SMART GRID-DEMAND SIDE RESPONSE MODEL TO MITIGATE PRICES AND PEAK IMPACT ON THE ELECTRICAL SYSTEM

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Abstract

Peak demand occurs when the maximum level of electricity is drawn from a network, and this demand is a major driver of increasing electricity market prices. In many cases, transmission and distribution networks must be sized to cope with the major increases in demand that occur for only a few hours on a few days of the year. A consumer-focused demand-side response (DSR) model can assist small electricity consumers, through an aggregator, to mitigate price and peak impact on the electrical system. The model proposed in the present research would allow consumers to independently and proactively manage peak electricity demand. Within this model, there is also the potential for benefit-sharing among both the consumer and the aggregator.

The aim of this thesis is to develop a demand-side response model which assists electricity consumers who are exposed to the market price through aggregator to manage the air-conditioning peak electricity demand. The main contribution of this research is to show how consumers can optimise the energy cost caused by the air-conditioning load considering the electricity market price and network overload.

This research examines how the control system applies the pre-cooling method in the case where a price spike may occur during the day. This method is also used to reach the minimum total expected market cost to avoid a price spike of electricity market. In addition, the control system applies this method to anticipate a price spike in the electricity market that may occur any five minutes during any day as well as to anticipate high costs due to the network overload. The spike probability is considered to define the minimum total cost.

To achieve this aim, numerical optimisation was applied to minimise the energy cost. The results indicate the potential of the scheme to achieve collective benefits for consumers and aggregators in order to target the best economic performance for electrical generation distribution and transmission. The model is tested with selected characteristics of the room, Queensland electricity market data

from the Australian Energy Market Operator and data from the Bureau of Statistics on temperatures in Brisbane, Queensland, during weekdays on hot days from 2011 to 2012.

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List of Abbreviations

A--Total area of room

AC--Air conditioning

AEMO—Australian energy market operator

A/S --Ancillary Service Market

B-- Heat transmission from the AC

COAG-- Council of Australian Government

CPP-- Critical Peak Pricing

CAP-- Capacity Market

C-- Cost

CB-- Collective Benefit

DSR-- Demand Side Response

DLC-- Direct Load Control

DB-- Demand Bidding

DNsP-- Distribution Network System Provider

EUAA-- Energy User Association of Australia

EDRP-- Emergency Demand Response Program

EZ-- Expected Market Cost

ET-- Expected temperature

EMC_{n1}-- Expected Market Cost when no spike occur before spike period

EMC_{n2}-- Expected Market Cost when no spike occur after spike period

EMCs-- Expected Market cost when spike occur

ETMC-- Total Expected Market Cost

EMCostn-- Total expected market cost without a spike occurring

EMCosts-- Total expected market cost assuming a spike occurring

H-- Heat capacity of the room

I/C-- Interruptible/Curtailable

K-- Penalty

k1-- Characteristic of the room

MC_{1}-- Total Market Cost without DSR program (half hour spike)

MC_{2}-- Total Market Cost without DSR program (one hour spike)

MC_{3}-- Total Market Cost without DSR program (one and half hour spike)

MC_{s}-- Total Market Cost Spike under DSR program

MC_{n}--: Total Market Cost no Spike under DSR program

NC-- Network cost

Ps-- High power

Pn-- Low Power

Pm-- Maximum power

P-- Rating power of AC

P_{D}-- Finite Probability

Q-- Heat transfer coefficient from floor wall and ceiling

RTP-- Real Time Pricing

RRP-- Regional Reference Price

Sn-- Electricity price (no spike)

Ss-- Electricity price (spike)

TOU-- Time of Use

Tmax-- Maximum Temperature

Tmin-- Minimum temperature

TMC-- Total Market Cost

TC-- Total cost under DSR program

TCo-- Total cost without DSR program

T_1-- Initial temperature

Ts-- Starting temperature

T-- Temperature room

t_1-- Initial time

ts-- Time to start

Tl-- Low temperature level

Th-- High temperature level

To-- Outside temperature

t'--Time of the end of spike

j-- Number of consumer

i-- Number of spike events

t-- time

U-- Continuous time of binary variable

W-- Demand

Wr-- Rating of transformer

Z--Minimised energy cost

α-- Constant value

$\in$-- Consumer

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

Name: Marwan Marwan

Signature:

Date: 30 October 2013

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Chapter 1: Introduction

This chapter outlines the introduction (Section1.1), background (Section 1.2) and research problem (Section 1.3) tackled in this study. Sections 1.4 and 1.5 describe the research aims and the significance of research. Finally, Section 1.6 provides an outline of the structure of the thesis.

1.1 INTRODUCTION

Contemporary competitive electricity markets mainly target the improved utilisation of the electricity infrastructure in order to reduce energy costs. This should lead, in the long term, to environmental and economic advantages and ultimately to reduced energy prices. However, current electricity markets have, in most cases, evolved to a state where the generation, transmission, distribution and retail entities are making market and operating decisions in isolation from consumers. Most electricity markets do not treat the consumer as a partner capable of making rational decisions, but simply as a load that needs to be served under all conditions [1].

In the current market, a limited number of consumers have the ability to reduce or reschedule their demand in response to electricity prices. For example, if prices are high, some industrial consumers may forego production if it is not profitable at that price level. Consumers who have the ability to store energy may reorganise their production [2]. Most of the current demand-side management programs exhibit common problems of low levels of consumer participation, poor managerial flexibility and poor real-time demand-side data [3].

It is generally agreed that consumers, at the tail-end of this market, inherently possess the ability to moderate the market price and avoid most of the currently experienced problems occurring mainly due to demand congestion, lack of coordination between consumers, and deficient use of generating capacities. With adequate information about basic economic and technical market operating conditions, consumers could contribute to the alleviation of demand congestion and achieve improved economic performance. This can be achieved by engaging consumers in incentive-based programs with monetary returns in cases where the consumer is observing market and network conditions and appreciating the value of energy relative to the appropriate time of use.

The intense and growing level of demand for electricity can lead to problems in the supply, such as daily and seasonal peak prices. Those recurring peaks in the electrical supply system can be associated with compromised quality, the risk of forced outages and high-priced energy. Demand-side response models are helping electricity users to proactively participate in reducing the problems associated with peaks. Coordinated DSR strategies are expected to help achieve the improved use of electrical energy, power plants and electricity infrastructure, as well as minimise energy costs for some appliances.

It is generally accepted that when there is a rapid growth in demand there is a potential for an increase in electricity prices. The market price for electricity in the peak season is higher than in the off-peak season. Another aspect of peaks is that there can be unpredictability in the electricity price. This usually happens because of an unexpected loss of a generator and/or damage to the transmission network.

To investigate the benefits of coordinated DSR strategies, the Queensland electricity market price was chosen for the case studies in the present study. Financial benefits are typically the primary consideration for the consumer and aggregator so these prices are used to demonstrate the minimisation procedure. Large customers can be directly affected by market prices and distribution charges. For a regulated customer, all the risk is taken by the retail company but if the customer is able to operate in recognition of market and network costs then the potential to collective benefits exists. In the present study, it was assumed that the customer is directly affected by these costs so that the potential collective benefit can be maximised. The research used the wholesale electricity market prices as published on the Australian Energy Market Operator (AEMO) website. Detailed information about the AEMO price data can be found in [4].

1.2 BACKGROUND

The Queensland total electricity generating capacity was 12487 MW at 31 December 2008 [5]. This power generation is used for residential, commercial and industrial consumers in Queensland. However, the amount of energy produced from various generators depends on market demand, price and availability of sources. In 2008, 81% of electricity came from coal-fired power stations, while 15% came from gas and 4% from renewable energy [5]. Figure 1-1 illustrates the components of electricity generation in Queensland.

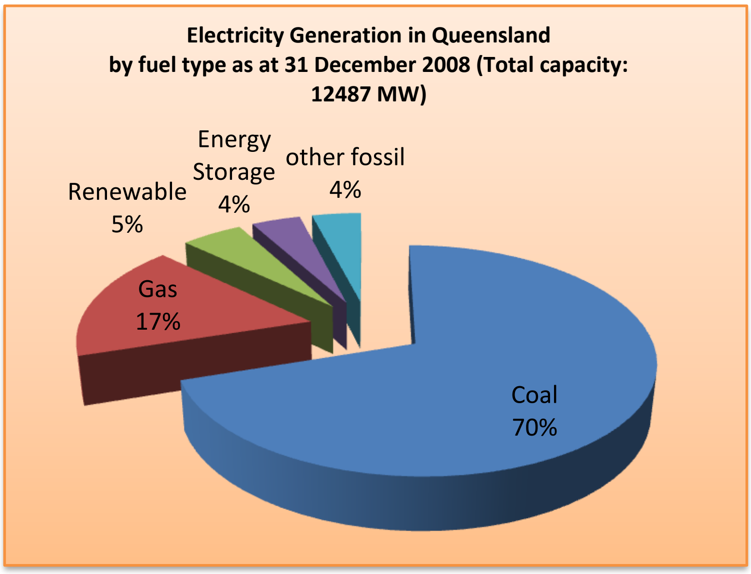

Figure 1-1: Electricity generation in Queensland [5]

Most of the power stations are directly connected to the transmission system. The Queensland electricity transmission system is provided by Powerlink which is licensed to operate a high-voltage transmission network of more than 12,000 kilometres, transporting electricity from the generators to the distribution networks as described by [6]. The distribution network carries electricity from the transmission system to consumers. In Queensland, ENERGEX and ERGON Energy purchase electrical energy from the Energy Market and distribute it to the customer. ERGON, for example, provides energy with several tariff options to end-users. For example, Tariff 11 for all domestic consumption is 18.84 ¢/kWh, the night rate Tariff 31 for all consumption is 7.7 ¢/kWh and the economy Tariff 33 for all consumption is 11.32 ¢/kWh [7].

The total energy consumption in Australia grew at an annual rate of 2.6% in the 25 years to 1997/1998 [8]. In the 2007- 2008 period, the annual electricity consumption in Queensland grew by over 29% or approximately 10500 GWh, making Queensland the second highest consumer of electricity in Australia [9]. This indicated that Queensland had a significantly greater number of high energy users than any other state, with most of these in regional Queensland.

Since the beginning of the 1990s, Australia's electric power industry has undergone a series of structural reforms [10]. In Queensland, the electricity industry was restructured in 1998 to prepare the industry for participation in the competitive National Electricity Market (NEM), which is responsible for the structure, rules and regulations regarding the delivery of energy to customers [11]. The National Electricity Market Management Company Limited (NEMMCO) was the wholesale market and power system operator for the Australian NEM. NEMMCO was established in 1996 to administer and manage the NEM, develop the market and continually improve its efficiency; from July 2009 it was replaced by the AEMO.

To improve governance, and enhance the reliability and sustainability of the states' electricity systems, the Commonwealth Government of Australia created a collaborative electricity and gas industry in the form of the Australian Energy Market Operator [12], which commenced operation on 1 July, 2009. The AEMO manages power flows across the Australian Capital Territory, New South Wales, Queensland, South Australia, Victoria and Tasmania. The electricity market in Western Australia and the Northern Territory are separately operated because they are electrically connected. The responsibilities of the AEMO include wholesale and retail energy market operation, infrastructure and long-term market planning, demand forecasting data and scenario analysis as described in [12]. The electricity market is comprised of a wholesale sector and a competitive retail sector. All electricity dispatched in the market must be traded through the central spot market. The market structure of NEMMCO/AEMO can be represented as shown in Figure 1-2.

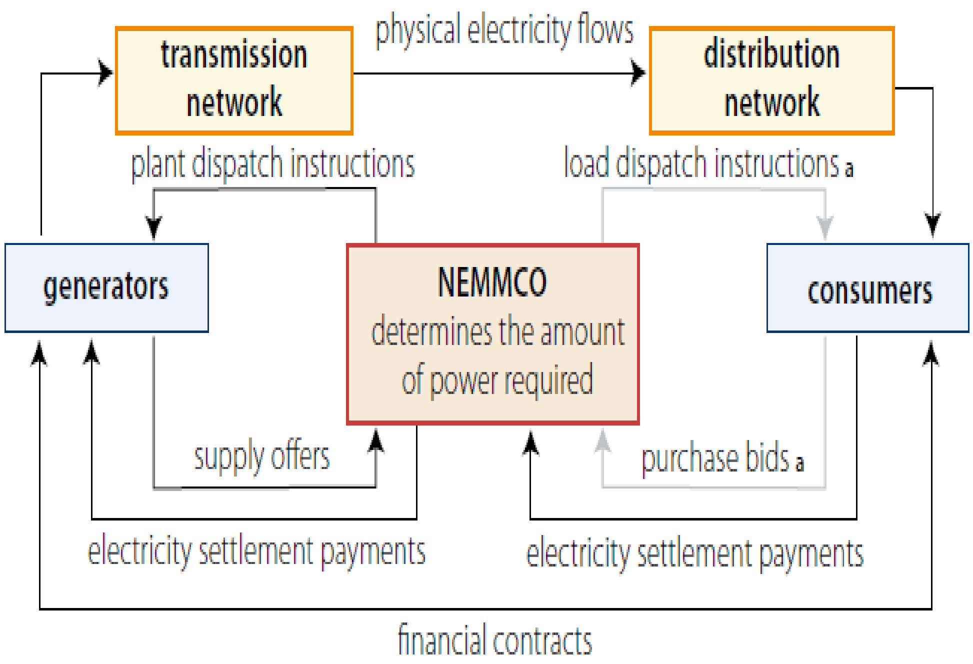

Figure 1-2: Market structure of NEMMCO/AEMO [13]

The strong economic and population growth in Queensland has largely contributed to significant increases in electricity demand in the residential and commercial sectors. Continuing to build and maintain inefficient buildings that rely on air-conditioning (AC) will compound the sectors' increased energy requirements. Each kilowatt of air-conditioning installed in Queensland costs up to $3000 in new energy infrastructure to meet peak demand [14]. All electricity users share these costs. The continued use of traditional supply mechanisms to meet projected peak demand is expected to cost approximately $15 billion by 2020 [14].

The increasing contribution of AC to energy consumption, and especially to peak loads, has received considerable attention in Australia in the past and will continue to do so in the coming years, from government, managers of energy efficiency programs, electricity suppliers and from electricity market regulators [15]. Managing demand on the electricity system in peak sessions is the most direct way to address the AC peak demand issue. Increasing the energy efficiency and improving thermal performance in both the residential and commercial sectors will also reduce peak demand on the electricity network.

It is clear from the data shown in Figure 1-3 that, in 2020, Queensland will be the largest consumer of cooling energy (44%) followed by New South Wales (27%). Western Australia and the Northern Territory will account for another 14% of consumption, leaving Tasmania and the Australia Capital Territory at 0% and 1%, respectively [16]. As a result, there will be a greater number of energy users in Queensland than in any other state in Australia.

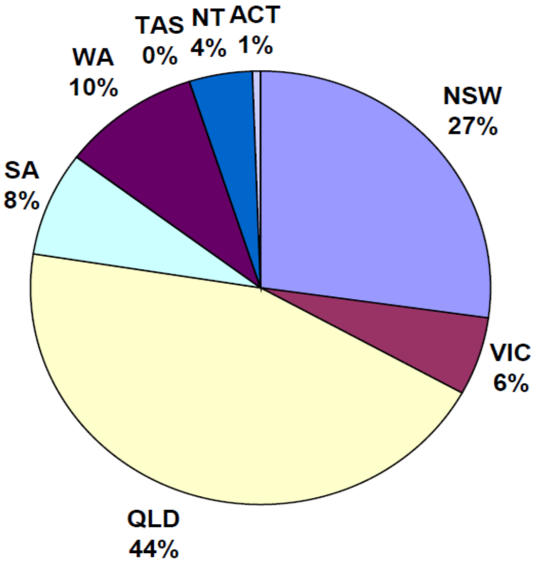

Figure 1-3: Projected cooling energy consumption share by state in Australia in 2020 [16]

The total growth of AC demand could be much higher because of the increasing dwelling area served and the increasing frequency of duration of use of AC. AC usage contributes greatly to peak load growth in both the commercial and residential sectors in Queensland. As illustrated in Figure 1-4, growth in energy is not equivalent to growth in demand. In South-East Queensland, energy growth was 28%, while demand growth was more than 55% in 2009-2010 [17].

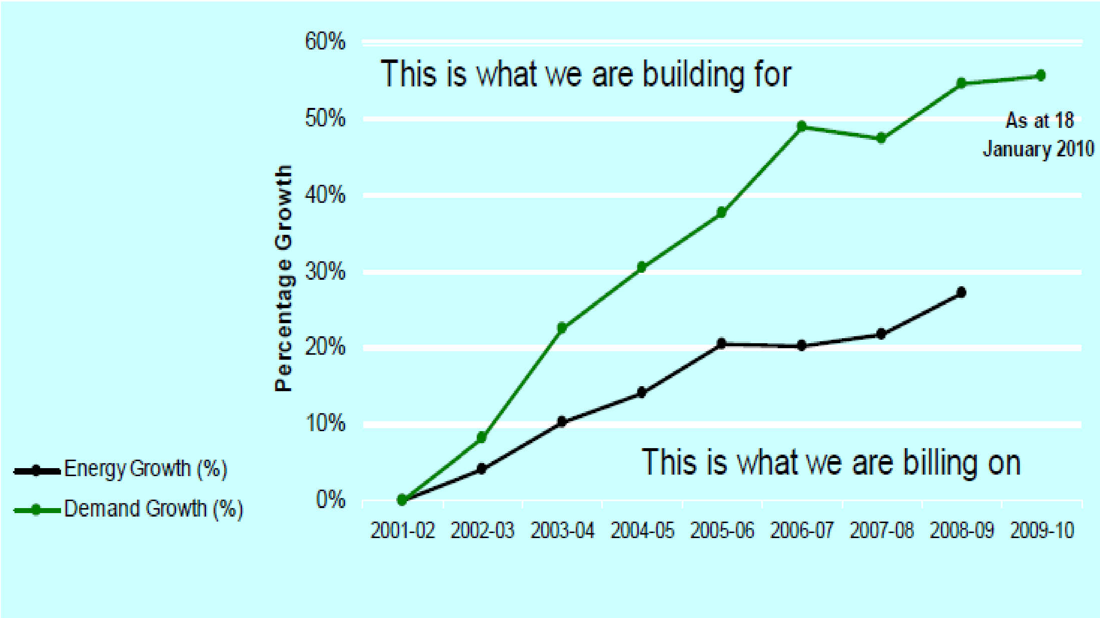

Figure 1-4: Energy growth and demand growth in South-East Queensland [17]

It is generally known that when there is a rapid growth in demand there is the potential for an increase in electricity prices. The market price for electricity in the peak season is higher than in the off-peak season. Another aspect of a peak is that it can cause unpredicted electricity spike prices. This usually happens because of an unexpected loss of a generator and/or damage to the transmission network.

Figure 1-5 indicates how air-conditioning uptake drives demands on the electricity network. At the time of writing, an estimated 79% of Queensland homes have air-conditioning installed, with close to three units on average per home, and the take-up is continuing to grow. Over the next five years, if penetration increases towards 90% as expected, over a billion dollars will need to be invested in the network to keep up with the demand for electricity in this sector alone [18].

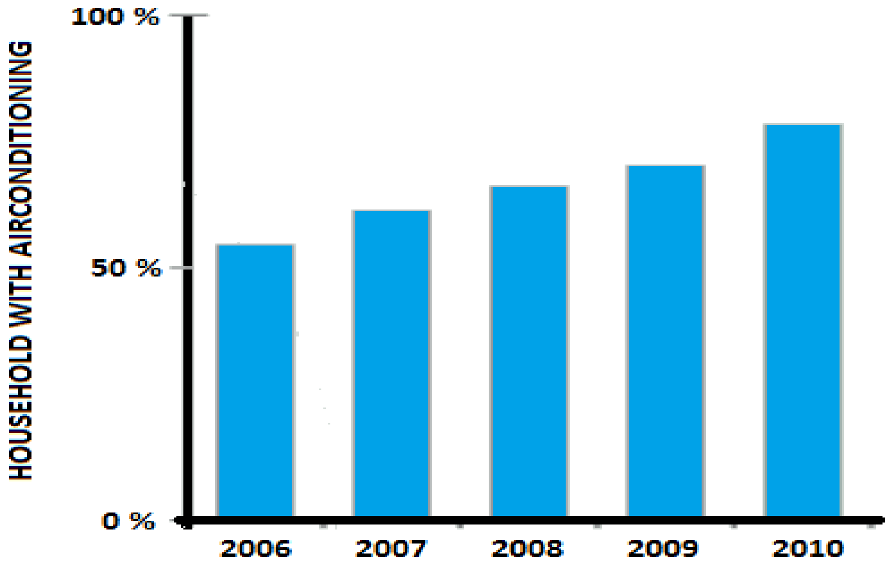

Figure 1-5: Percentage of households in Queensland with air-conditioning [18]

1.3 RESEARCH PROBLEM

Peak demand is a major driver of increasing electricity market prices. Peak demand refers to the times when the maximum level of electricity is drawn from the network. In Queensland, peak demand generally occurs on hot days. On hot summer days, significant increases in demand occur due to the widespread use of air-conditioning [19]. This means a price spike will be more likely on hot days. Price spikes often occur during a day when ambient temperatures increase, resulting in a significant increase in the use of air-conditioners. There is an increased cost with respect to energy markets when many air-conditioners operate at the same time. In addition, the transmission and distribution networks must be sized to cope with major increases in demand that normally occur for only a few hours on a few days of the year.

1.4 RESEARCH AIMS

This research aimed to develop a consumer-focused DSR model to assist small electricity consumers, through an aggregator, to mitigate price and peak impact on the electrical system. The proposed model would allow consumers to independently and proactively manage air-conditioning peak electricity demand. The main contribution of this research is the development of mechanisms by which the small consumer can mitigate price and peak impact on the electrical system by optimising energy costs for air-conditioning to achieve energy savings. The potential for benefit-sharing among both the small consumer and the aggregator exist (collective benefit). In addition, this study investigated how the pre-cooling method can be applied to air-conditioning when there is a substantial risk of a price spike and feeder overload. To achieve this aim, the objectives of research project were identified as:

1. To understand how to minimise energy costs for air-conditioning if spikes may occur in the middle of the day.

2. To define the total expected cost for the air-conditioning if spikes may occur only on the hour during a day.

3. To identify how to minimise energy costs for air-conditioning if spikes may occur every five minutes during a day.

4. To identify how to minimise energy costs for air-conditioning based on electricity market and network congestion cost.

1.5 SIGNIFICANCE OF THE RESEARCH

A review of the literature reveals that a wide range of efforts are undertaken by electricity suppliers to alleviate peak demands. The present research develops a new model to be used by small consumers to mitigate price and peak impact based on the electricity price signal. The price signal can encompass the issues of the electricity market price and feeder overloading. This research will assist to achieve financial collective benefits for the small consumer and aggregators and help to promote the optimal economic performance for electrical generation distribution and transmission.

1.6 THESIS OUTLINE

Chapter 1 introduced the electricity market and the potential of consumer participation in the electricity market under the smart grid system. An overview of the research problem, research aim and significance of research was presented.

Chapter 2 presents the literature review. Three main subject areas in the literature are discussed including the concepts of electricity price and demand, price spikes in the electricity market and demand-side response initiatives.

Chapter 3 describes the application of the market price to small consumers (aggregators).

Chapter 4 sets out the methodology, including numerical optimisation, selection of typical room and air-conditioning, and data processing.

Chapter 5 describes the framework of the research as derived from the literature review. In addition, the DSR model-1 is presented, defining the minimum cost of air-conditioning if spikes occur in the middle of the day.

Chapter 6 demonstrates the DSR model-2 to define the expected cost for air-conditioning if spikes in the electricity price occur on the hour.

Chapter 7 demonstrates the DSR model-3 to define the total cost of air-conditioning if spikes occur at any five minutes during a day.

Chapter 8 demonstrates the DSR model-4 to define the total cost of air-conditioning based on the electricity market price and network cost.

Chapter 9 presents the conclusions and recommendations for future work.

Chapter 2: Literature Review

2.1 INTRODUCTION

This chapter begins with an introduction (section2.1), an overview of electricity price and demand (section 2.1), describing electricity market price, network cost and electricity demand. Then follows a review of literature on the following topics: a price spike of electricity market (section 2.3), this section describe the meaning of a price spike, some factors can cause of a price spike, how to define a price spike and an example of a price spike electricity in Queensland; smart grid-demand side response (section 2.4) this section describe overview of smart grid-demand side response, the meaning of smart grid and DSR, benefit of DSR, how DSR is applied in Australia and others countries, categorization of DSR as well as DSR and air conditioning; and a conclusion (section 2.5) describing conclusions from the literature review.

2.2 ELECTRICITY PRICE AND DEMAND

As explained in Chapter 1, AEMO is a wholesale market management company through which generators sell electricity in eastern and southern Australia. The main customers are big consumers and energy retailers, which bundle electricity with network services for sale to residential, commercial and industrial energy users. The wholesale electricity market prices and demand are published on the AEMO website. Detailed information about AEMO market price and demand data can be found in [4].

2.2.1 Market Price

The electricity market price can be separated into two parts, namely, the normal price and the spike price [20]. The normal prices usually occur in the morning or off-peak season. In these periods, the electricity generation is sufficient to cover electricity needs for the consumer since there are no high demands from the consumer and typically no major generator failures and no congestion on the transmission and distribution network. In addition, when the supply is large enough, the price is found to be distributed in a low range and there is no occurrence of price spikes [21]. Therefore, the electricity price is based on the base price at that time.

The actual energy price and demand conditions in the relevant regions are regularly released every 30 minutes on the Internet by the AEMO. Figure 2-1 depicts an example of fluctuations in electricity market price and demand in Queensland for the period from 16:00 on 28 November, 2012 to 04:00 on 1 December, 2012. The market price pattern has characteristics similar to that of the demand but with much higher volatility. The electricity price is typically at its lowest level during times of low demand (off-peak); for example, at night. For most residential consumers, the electricity prices passed on by the retailer are typically on a flat rate regardless of the time of day.

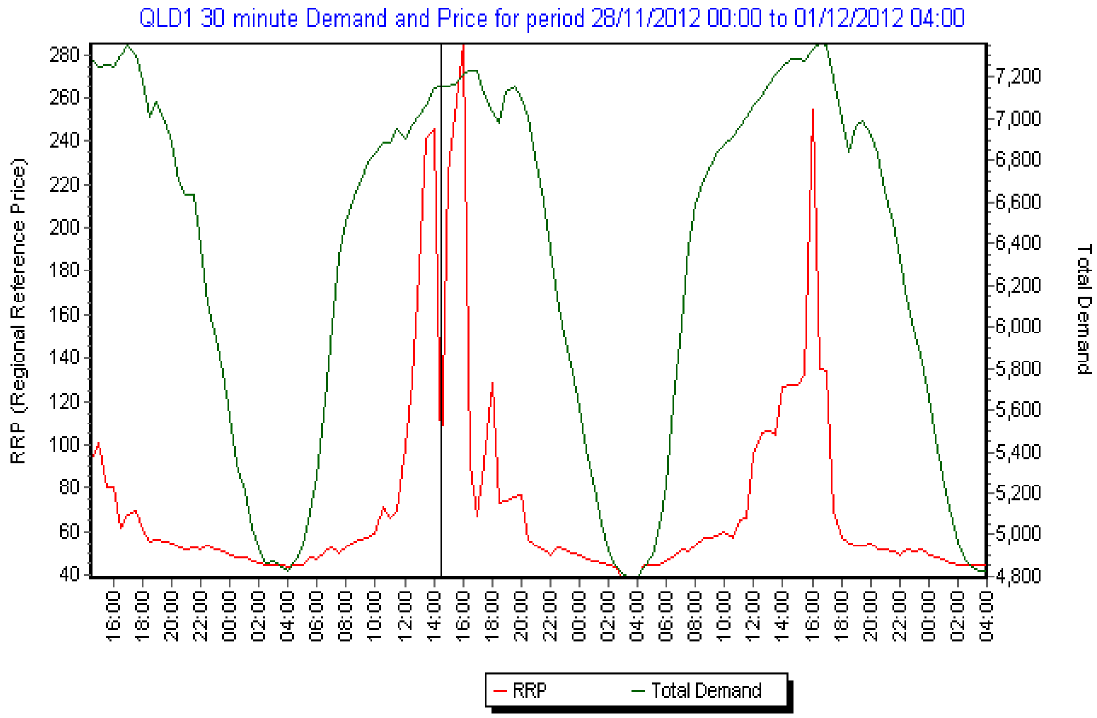

Figure 2-1: Wholesale electricity price and demand in Queensland from 28 November to 1 December, 2012 [4]

Figure 2-2 indicates an example the Queensland electricity market price during the summer periods from 2010 to 2012. In 2010, the electricity market price in January was higher than in February and March. The electricity market prices in January, February and March were A$58 per MWh, A$39 per MWh and A$25 per MWh, respectively. In 2011, the electricity market price in February was higher than in January and March. The electricity market prices in January, February and March were A$44 per MWh, A$105 per MWh and A$72 per MWh, respectively. In 2012, the electricity market prices were lower than in the previous year. In January the price was A$32 per MWh, in February it was A$30 per MWh and in March it was A$27 per MWh. As a result, the average electricity price during 2012 was A$31.09 per MWh, significantly lower than in 2011 and 2012.

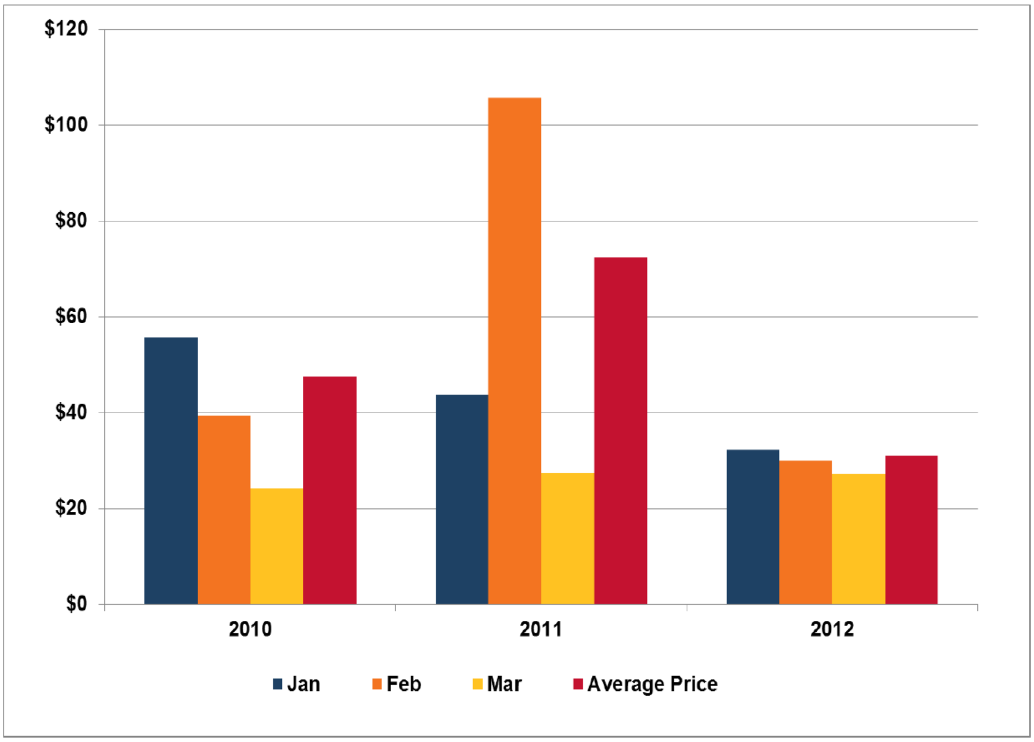

Figure 2-2: Average Queensland summer, 2010 to 2012 [22]

2.2.2 Network Cost

Network cost is the total cost which required to distribute electricity from generator to the consumer through transmission and distribution line. This cost is the largest cost component as this represent the cost of build and maintain the electricity delivery system to the consumers. The costs considered include: operational and maintenance expenditure, a return on capital, asset depreciation costs and tax liabilities [23]. Therefore, this cost is usually set up from the government every particularly time, e.g. every 5 year.

Network cost is one of the key factors that contribute to the current increase and predicted future in electricity price. Electricity price increases are largely being driven by rising network charges, reflecting the need to expand network capacity, replace ageing assets, meet higher reliability standards and cover higher input and borrowing costs [23]. The network cost is taken from the distribution and transmission network charges. Transmission charges is about 10 per cent of retail prices, while distribution charges is about 35 to 50 per cent [23].

2.2.3 Electricity Demand

Growing electricity demands followed by constantly growing supply lead to troubled electrical services manifested by technical and economic deficiencies and alleged critical environmental impacts [24]. Technical and economic difficulties are mainly represented in congestions at peak demand times associated with compromised quality (e.g., voltage drop) and high-priced energy [24]. In low demand periods (e.g., at nights), the resulting low energy cost could drive power plants to operate at the limits of economic viability. The situation came to the point at which electrical suppliers, at their end, needed an operating scheme in which they could identify and prioritise demand while users, at the other end, needed to be aware of the suppliers' capabilities and network conditions in order to be able to decide about purchasing electricity at a certain time and price. Recognising the limits of the consumer-supplier interaction conditions helps to achieve improved electrical supply services.

Electricity demand growth is a significant problem in relation to the expected population increases in the foreseeable future. This demand in growth is expected to continue in line with population growth every year [25, 26]. For example, the population of South-East Queensland increased by 33% in the 12 years to 2009, and peak electricity demand increased by 99% in the same period [27]. Figure 2-3 shows an example of an actual energy demand situation in Queensland. The price curve follows the demand curve closely, reflecting the fact that generators at lowest operating cost are in fact providing base load power, twenty-four hours a day, while peak loads exceeding the base load are usually covered by the more expensive plants, for shorter periods [13]. Electricity demand typically decreases to the lowest level at night during the off-peak session. In contrast, the electricity demand is rising based on the peak session in the midday and afternoon.

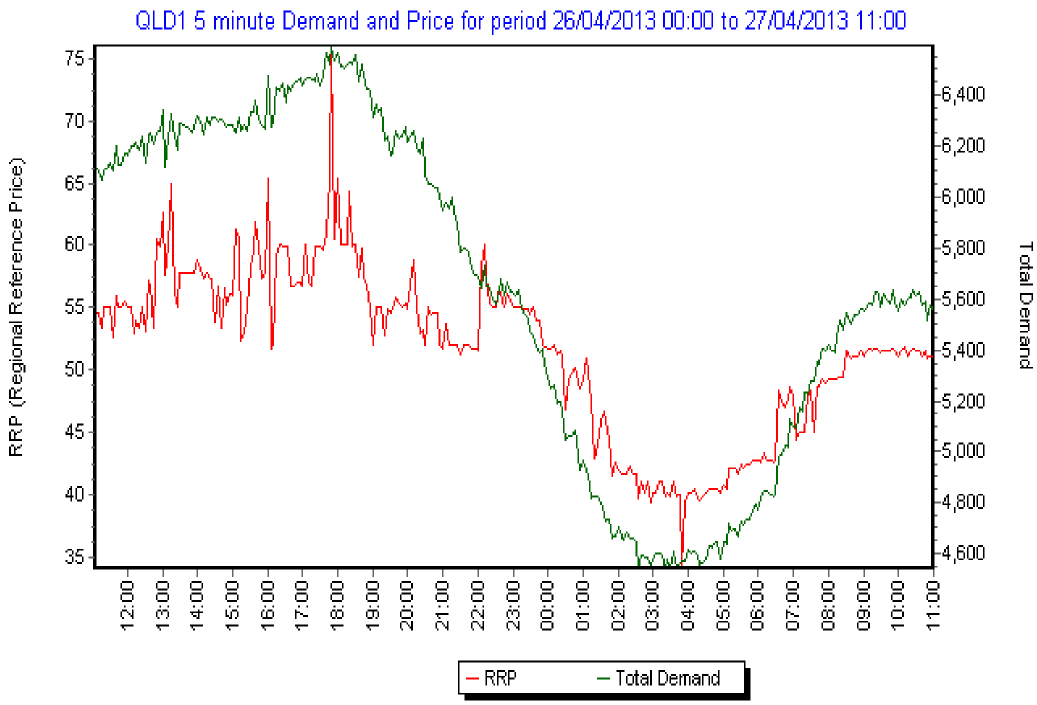

Figure 2-3: Wholesale electricity price and demand in Queensland from 26 April to 27 April 2013 [4]

Seasonal climate variation has a significant impact on the operation of electrical power systems. Due to the temperature rises in summer, the electricity demand will increase with the load of air conditioning or other appliances. Moreover, if the consumers all turn on the air conditioning at the same time, then the total demand will be increased. Temperature is an important driver for electricity consumption. More than 40% of end-use energy consumption is related to the heating and cooling needs in the residential and commercial sectors [28]. The following Figure 2-4 indicates the electricity demand and temperature situation on 9

January 2012. This figure indicates the pattern of demand following the form of temperature. The temperature increased at 09.00 to be 30°C followed by an electricity demand of 7500 MW. This situation does not just occur on one day but also on many other days, as given in Figure 2-5.

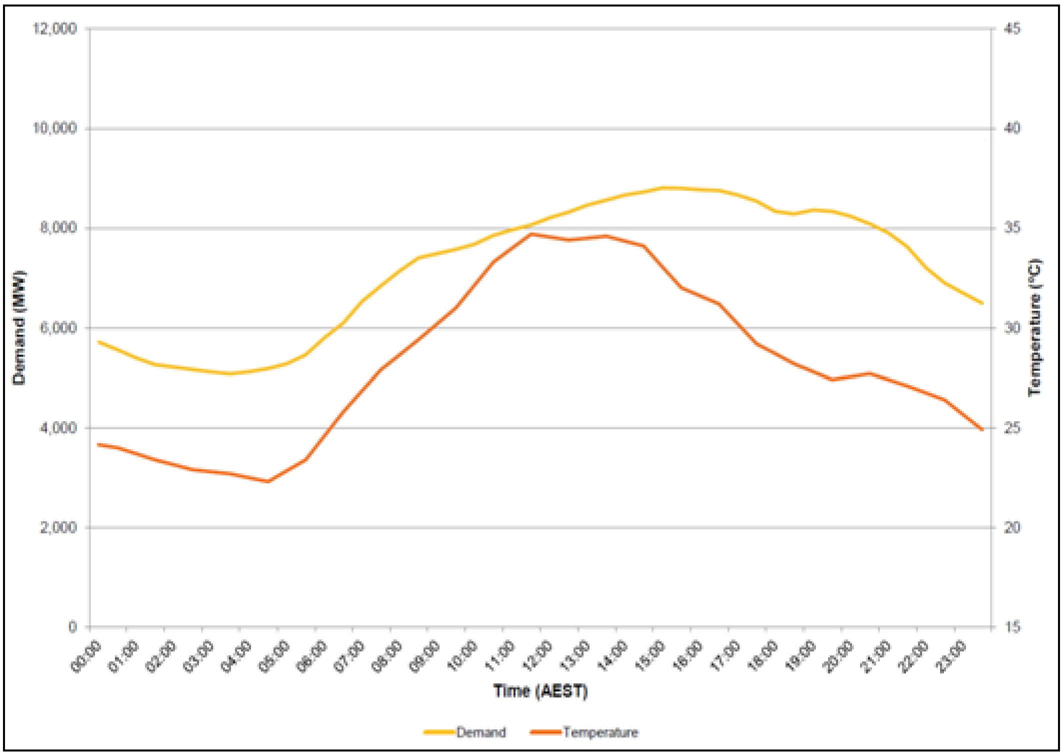

Figure 2-4: Electricity demand and temperature on 9 January 2012 in Queensland [29]

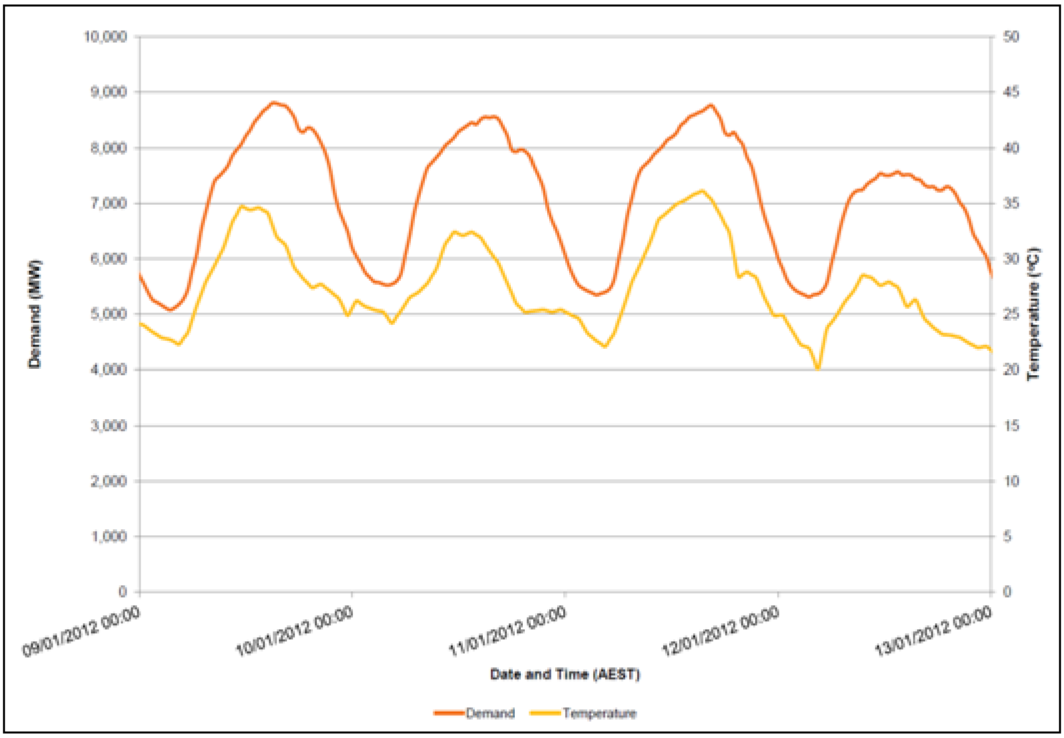

Figure 2-5: Electricity demand and temperature from 9 January to 13 January 2012 [29]

2.3 PRICE SPIKES IN THE ELECTRICITY MARKET

A price spike can be generally defined as an abnormal price value, which is significantly different from its expected value [30, 31]. The price spike in the electricity market is an abnormal market clearing price at a time point t and is significantly different from the average price. The price spikes could rise 100 or 1000 times higher than the normal price, which brings a high risk for the market participants [21]. This impact is on any market exposed consumer, including the electricity retailer.

On the basis of this definition, price spikes may be classified into three categories [30, 31]:

1. Abnormal high price – a price that is significantly higher than its expected value.
2. Abnormal jump price – if the absolute value of difference between electricity price values in two successive time intervals is greater than a jump threshold (JTH), we have

$$|\mathrm{P(t)} - \mathrm{P(t-1)}| > JTH \quad (2.1)$$

then P(t) is defined as a price spike of the abnormal jump price type.

3. Negative price – a price value lower than zero is defined as a negative price.

There are many factors that can cause a price spike. In general, the underlying causes may include [32]:

1. High demand that requires the dispatch of high cost peaking generators.
2. A generator outage that affects regional supply.
3. Transmission network outages or congestions that restrict the flow of cheaper imports into a region.
4. A lack of effective competition in certain market conditions.

In the deregulated electricity market, the price spikes are highly randomized events, it can be caused by market power and unexpected incidents. The price spikes can be influenced by many complex factors including physical characteristic of the system, supply demand, fuel prices, plant operating costs and weather conditions. The most significant factor theoretically is the balance between overall system supply and demand. Therefore when demand is larger than the supply, or the supply lower than demand, the price spike will occur[33].

In the current methods, price spikes are determined by the following approaches [20]:

1. Based on statistics, the outlier price is calculated from the historical dataset. Let μ be the mean value of the historical dataset, δ be the standard deviation of the dataset, and Pv be the abnormal data threshold value of the sample dataset. Pv can be calculated by:

$$Pv = \mu \pm 2\delta \quad (2.2)$$

Any regional reference price (RRP) > Pv is regarded as an outlier price type of price spike.

2. Based on the experience with electricity market prices, the abnormal high price can be determined. An abnormal high price threshold value $P\tau$ can be calculated based on the probabilistic distribution of electricity prices in each electricity market. If

$$\text{RRP} > P\tau \quad (2.3)$$

then this particular RRP is regarded as an abnormal high price type of price spike.

3. The abnormal jump price can be calculated by examining the price difference between two neighbouring time prices. Let the current time price be RRP(i) and the previous time price be RRP(i − 1), the difference at time i is _RRP(i) = |RRP(i) − RRP(i − 1)|. Let_P be the maximum jump different price in the normal price range, then for any _

$$\text{RRP}(i) > \Delta P \quad (2.4)$$

the current time price RRP(i) is regarded as an abnormal price jump type of price spike.

4. The negative price refers to negative RRPs, that is, any

$$\text{RRP} < 0 \quad (2.5)$$

is regarded as a negative price type of price spike.

Figure 2-6 summarises the electricity price fluctuations in Queensland from 1 January 2012 to 31 March 2012. The graph illustrates pricing events when the 30 minute spot price was above or below A$300 per MWh. There were 17 pricing events reported for Queensland during this period. The graph also indicates that the extreme regional reference price during that period occurred three times in January 2012. However, the maximum price of A$2892 per MWh (¢289.2/kWh) occurred on 10 January 2012 at 14:00. On 29 January 2012 at 14:30, the price rose to A$2079 per MWh (¢207.9/kWh) and between these peaks, a high of A$1757 per MWh (¢175.7/kWh) occurred on 12 January 2012 at 10:00.

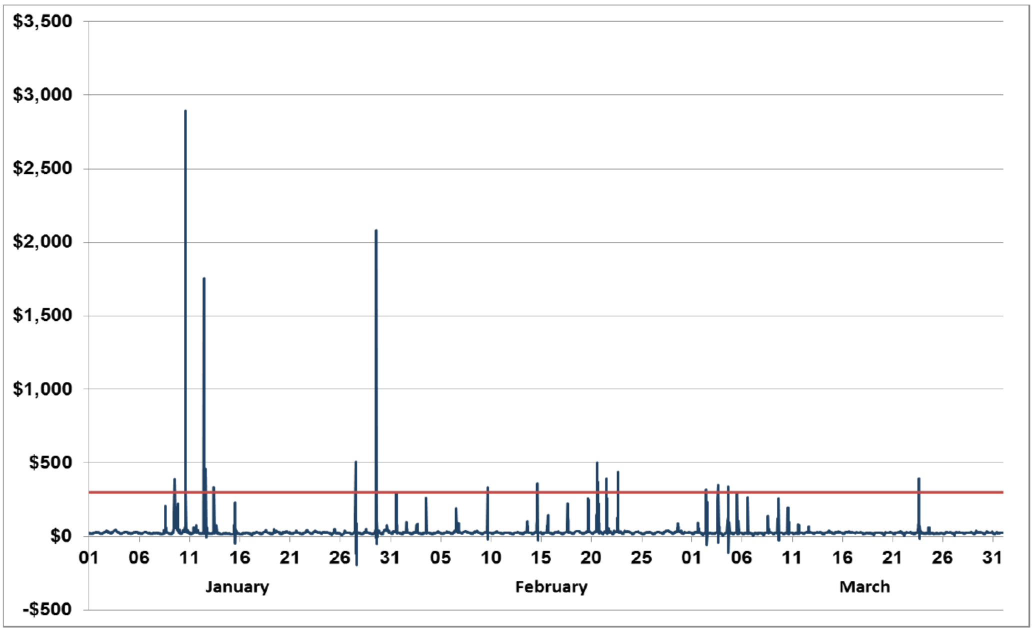

Figure 2-6: Queensland 30 minute price from 1 January 2012 to 31 March 2012 [34]

2.4 SMART GRID DEMAND-SIDE RESPONSE

2.4.1 Smart Grid

The smart grid refers to a system that comprises intelligent electricity distribution devices communications, advanced sensors, automated metering and a specialized computer system to enhance reliability performance, enhance customer awareness and choice, and encourage greater efficiency decisions by the costumer and the utility provider [35]. The smart grid includes two way communication will allow the consumer to better control their energy usage and provide more choices to the customer, and furthermore, the two-way communication will also allow better demand-side management such that in certain situations the system operator can be given control of the loads in the system, enabling more agile responses to system behaviour[36]. Therefore under the recent trends of developing smart grid systems, demand side response issue has been raised again as one of the important methods of energy saving [37]. The concept of the smart grid is the electric grid delivers electricity in a controlled smart way from points of generation to consumers [38]. Therefore, using this technology will improve reliability, efficiency and responsiveness of the electrical power system.

The smart grid system is an expression for contemporary electrical energy supply system that allows appropriate demand-side-response to control the electricity usage using innovative technology. The following Figure 2-7 indicates an example of a smart grid demonstration project initiative. The system automatically evaluates fluctuating power-generation costs and electricity-market prices to determine optimized incentives for customers to saving power, thereby helping to stabilize supply and demand side response while minimizing costs and benefits for utilities and customers alike [39]. Therefore to decrease power consumption during peak demand, the utility and consumer should be expected from implementing demand side response which offer incentive or reward to the consumer in exchange for curtailed their use of power.

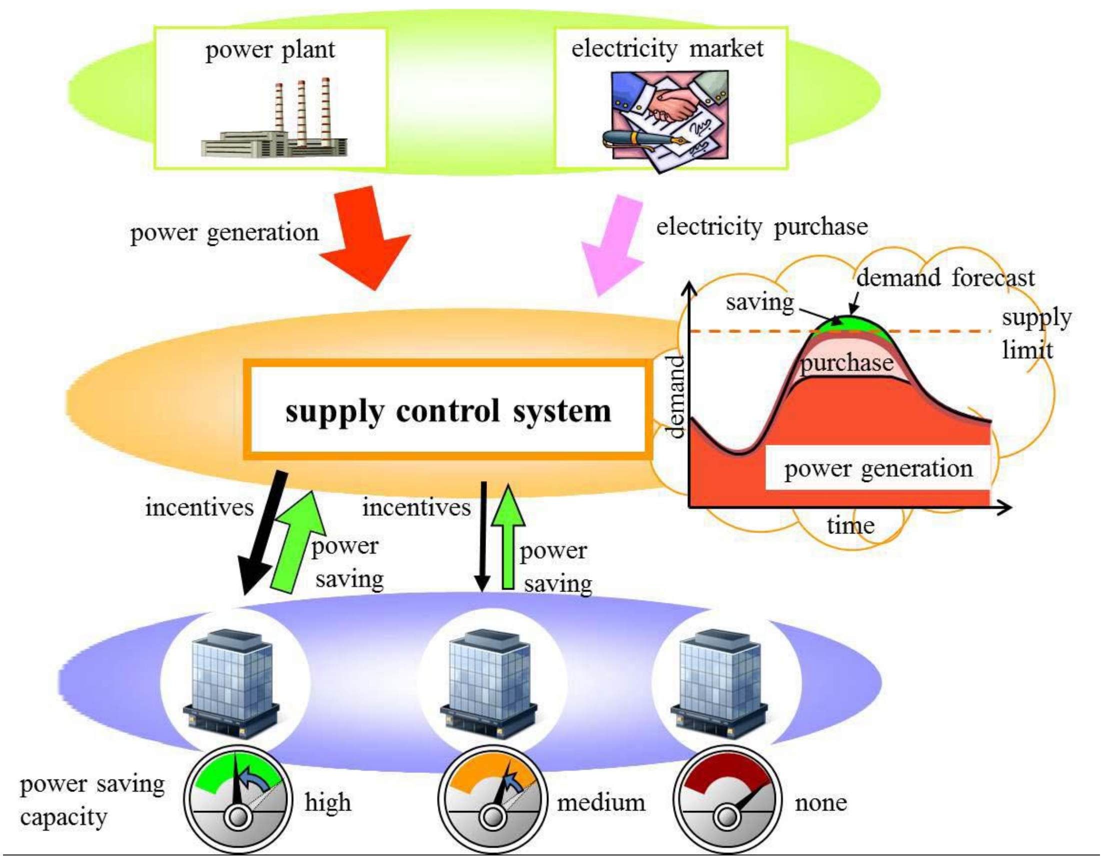

Figure 2-7: Example of smart grid demonstration project initiative [39]

2.4.2 Demand-Side Response

In a smart grid system, consumers are an integral part of the power system, wherein they are encouraged to participate in the system's operation and management. From the perspective of market operators, controllable demand is another resource; it will help to balance supply and demand to ensure system reliability. The mechanism of the smart grid offered to the consumer is to transform the energy consumption into economic choice [3].

Demand Side Response (DSR), as described by [40] can be defined as the changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity or other incentives over time. [41] describes DSR as a tariff or program established to motivate change in electric consumption by customers in response to change in the price of electricity over time. Further on, DSR programs provide means for utilities to reduce the power consumption and save energy, maximize utilizing the current capacity of the distribution system infrastructure, reducing or eliminating the need for building new lines and expanding the system as described by [42].

The benefits of DSR programs apply to consumers and to electricity providers collectively. Some advantages are: increased economic efficiency of electricity infrastructure, enhanced reliability of the system, relief of power congestions and transmission constraints, reduced energy price, and mitigated potential market power [43]. DSR, as an integral part of the smart grid, is a cost-effective, rapidly deployable resource that provides benefits to utility companies and customers [44]. DSR can help reduce peak demand and therefore reduce spot price volatility [45]. DSR participation would help electricity power markets operate in a more efficient way [46]. The seven overall categories of the benefits of a DSR program are: economic, pricing, risk management and reliability, market efficiency impacts, lower cost electric system and service, customer service, and environmental benefits [47], as given in Figure 2-8.

Figure 2-8: Benefits of DSR [47, 48]

From the consumer perspective, applying DSR program will assist consumer to obtain benefit through minimised energy cost without reducing their total usage of power. Curtailing or shifting energy consumption is also an effective way for consumers to avoid expensive costs and reduce their electricity bill. This advantage is not just to the consumer but also to the utility company, as implementing a DSR program can abate the wholesale electricity market price because of the reduction of the demand. As a result, the expensive generation unit will be reduced [48, 49]. In addition, one of the other advantages of DSR in the pricing area is that it mitigates price volatility and hedges cost reductions [47].

Based on a review of current utility programs, the Electric Power Research Institute estimated that DSR had the potential to reduce peak demand in the United States by 45,000 MW [50]. Most importantly, by enabling end-users to observe electricity prices and congestions on the electrical network, it allows users to positively share responsibility by reducing and optimising energy consumption and experiencing electricity savings [51]. Therefore, the implementation of DSR programs can be expected to improve economic efficiency in the wholesale electricity market.

In Australia, implementation of the DSR programs was conducted a number of years ago. In late 2002, the Energy Users Association of Australia conducted a trial to demonstrate the benefits of a DSR aggregation process which would enable electricity consumers to respond to both the extreme prices and extreme peak demands [52]. This experiment was conducted by consumers to determine the value of an effective DSR and its impact in terms of supporting an energy saving program. The project was supported by the Victorian, New South Wales, and Commonwealth Government, as well as the Commonwealth Scientific and Industrial Research Organisation **(**CSIRO**),** to implement a Demand Side Response Facility [52].

In the experiment described above, the Australian Government through the EUAA invited consumers to participate in the DSR trial. This experiment was conducted in three regions that fell under the National Electricity Market operation, namely, New South Wales, South Australia and Victoria [53]. These areas were regarded to represent the electricity load in Australia, and the results showed some significant benefits of using DSR for consumers and electricity providers. Hence, in December 2003, the Ministerial Council for Energy advised the Council of Australian Governments (COAG) on the need for further reform of the energy market to enhance active energy user participation [53].

The Energy Users Association of Australia reported that South Australian electricity consumers, for example, only used the highest 10% of their maximum electrical demand on the network less than 0.5% of the time per year, that is, for about 40 hours per year [52]. The EUAA report stated further that while the electricity consumers were insulated from price volatility by ‘flat’ electricity prices, they were also paying a significant and undisclosed (hard to evaluate) premium on their retail electricity prices to cover the retail supplier’s costs of managing the risks of the extreme price volatility.

It is very important to electricity consumers and the Australian economy that electricity costs are minimised. DSR is an effective way to ensure cost effectiveness and address peak demand. The need for customer awareness of the opportunities from DSR is critical and projects like the one conducted by the EUAA play an important role in demonstrating the benefits that can be achieved.

The following set of objectives was established for this project [52]:

1. To make electricity consumers more aware that there are commercial and broader economic benefits from effective DSR; and
2. To determine through practical Case Studies, those electricity consumers who can gain significant benefits from relatively small and occasional responses to extreme NEM prices and demands, or peaks in network demand, and the extent of those benefits.

In the United Kingdom, various techniques have been used to develop load electricity management. One of the methods, developed in the early 1960s, is called the responsive demand or demand-side management program [54]. This system served to maintain the security of the electricity supply and limited the facilities for electricity generation, transmission and distribution. This program aimed to improve the economy, security and reliability of the electricity industry and address the environmental concerns [54]. Later, in 2007, the British Government initiated the Energy Demand Research Project which focused on the actual benefits of demand response for consumers [55].

The British Government has continued to consider the economic benefits of a demand-side response program, as such a system requires a high implementation cost. In addition, the government has first sought to conduct reform of the electricity industry to support a demand-side response program by restructuring the electricity price and market, transmission and distribution as well as the retail sector. According to [55], much of the debate around the economic potential of demand-side response focuses on the actual benefits of DSR for consumers, with benefits and weaknesses for both the government and the user. Hence, there are five technology specifications that a DSR project can potentially comprise such as: a minimum meter specification, smart meters that substitute old meters, dumb meters combined with smart boxes, retrofitted devices, and clip-on consumer display units [55].

Similar to what has occurred in the UK, interruptible programs as a part of the demand-side response model have been used in Finland for several years as a disturbance reserve [55]. Utilisation of this demand-side response program has been effective to overcome peak load, breakdown and manage the electricity supply to all customers. This plan is not just applied by small consumers but also has been used by large-scale industry. In 2005, the total demand-side response potential in Finnish large-scale industry was estimated at about 1280 MW, which represented 9% of the Finnish power demand peak [56]. Following that, in 2008, the Finnish main electricity utility invested in an advance metering reading system to automatically read, control and manage all 60,000 of its customer metering points [55].

In Korea, a demand-side management program has been used for several years. In the 1970s, several programs were introduced in load management, for instance: the night thermal-storage per rates program (1972), inverted block program (1974), the seasonal tariff (1977) and the time of use tariff (1977) [57]. However, the program did not reach the maximum results to control the load demand for peak demand sessions. Therefore, in 2006, after the revision of the law, the government announced its 3rd National Electricity Demand Forecast and Supply Plan which addressed the government’s main concerns about the demand-side management [57].

2.4.3 Demand-Side Response Model

Many different economic models are used to represent DSR. DSR programs are divided into two basic categories, namely: time-based programs, and incentive-based programs [58]. The specific types of time-based programs are: time of use (TOU), real-time pricing (RTP) and critical peak pricing (CPP) [59]; while the specific types of incentive-based programs consist of direct load control (DLC), interruptible/curtailable (I/C), demand bidding (DB), emergency demand response program (EDRP), capacity market (CAP) and ancillary service markets (A/S) programs [60]. Figure 2-9 illustrates the categories of DSR programs. A brief description of four popular programs – the TOU, RTP, I/C and EDRP model – is provided in the following sections.

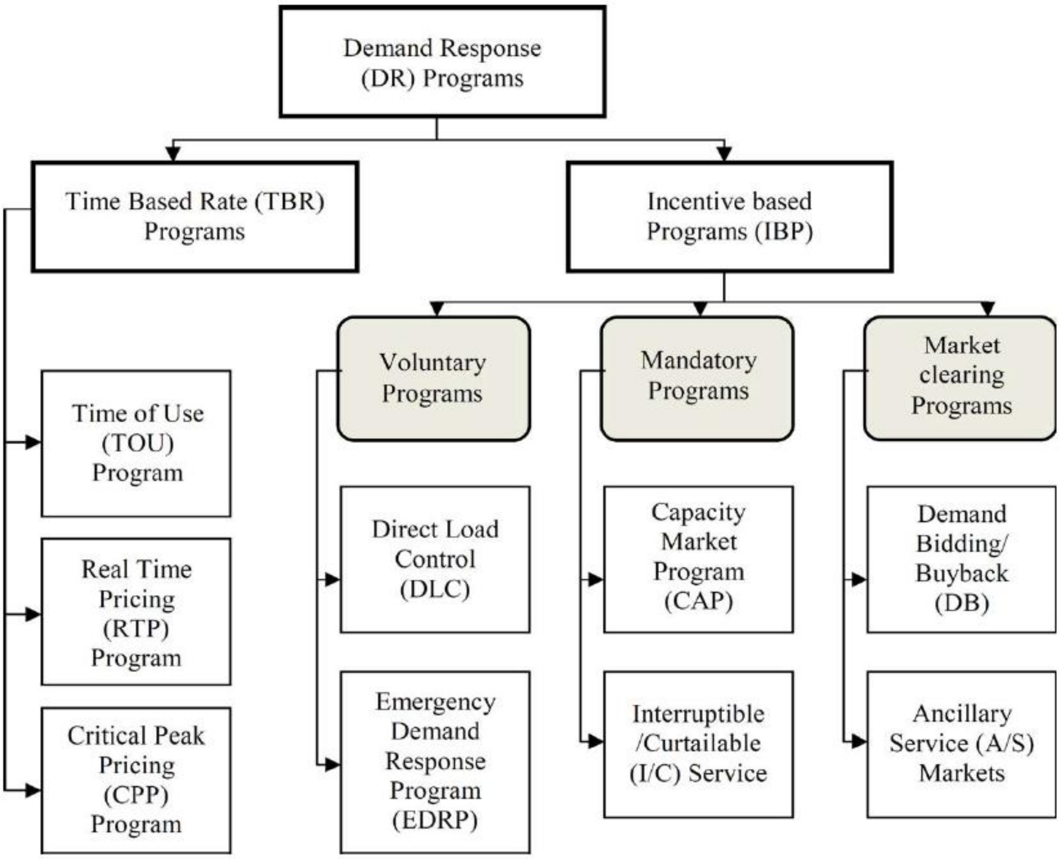

Figure 2-9: Categories of demand-side response programs [49, 61]

2.4.3.1 Time of Use

TOU is one of the important demand-side response programs which responds to price and is expected to change the shape of the demand curve [62]. The TOU rate is the most obvious strategy developed for the management of peak demand, and is designed to encourage the consumer to modify their patterns of electricity usage [63]. To apply this type of program, the utility company does not provide rewards or penalties to consumers. To participate, all consumers are required to remove their energy consumption during peak sessions to off-peak sessions as soon as they receive information from the utility company [24]. The type of contract and the rate is fixed for the duration of the contract but depends on the time of the day [1].

Compared to the flat rate contract, some of the risk is shifted from the retailer to the consumer because the consumer has an incentive to consume during periods when the rates are lower. Figure 2-10 illustrates the type of hourly price variation consumers would face under the different TOU rates.

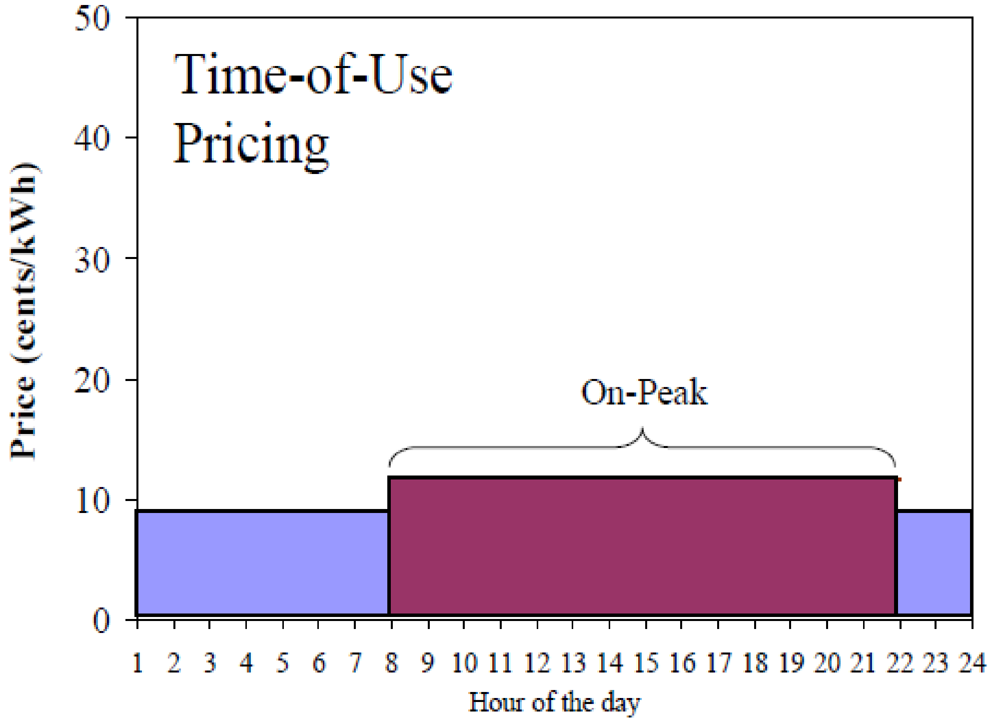

Figure 2-10: Time of use pricing [60]

2.4.3.2 Real-Time Pricing

The RTP program gives consumers the ability to access hourly electricity prices that are based on wholesale market prices. These prices vary from hour to hour and day to day according to the actual market price of power. Higher prices are most likely to occur in peak session times (e.g., 11.00-17.00). The consumer can manage the costs with real-time pricing by taking advantage of lower priced hours and conserving electricity during hours when prices are higher [60]. Additionally, the RTP program allows consumers to achieve energy savings by curtailing their marginal use at times when prices are higher and by using more during the off-peak tariff times. Figure 2-11 illustrates how the RTP operates.

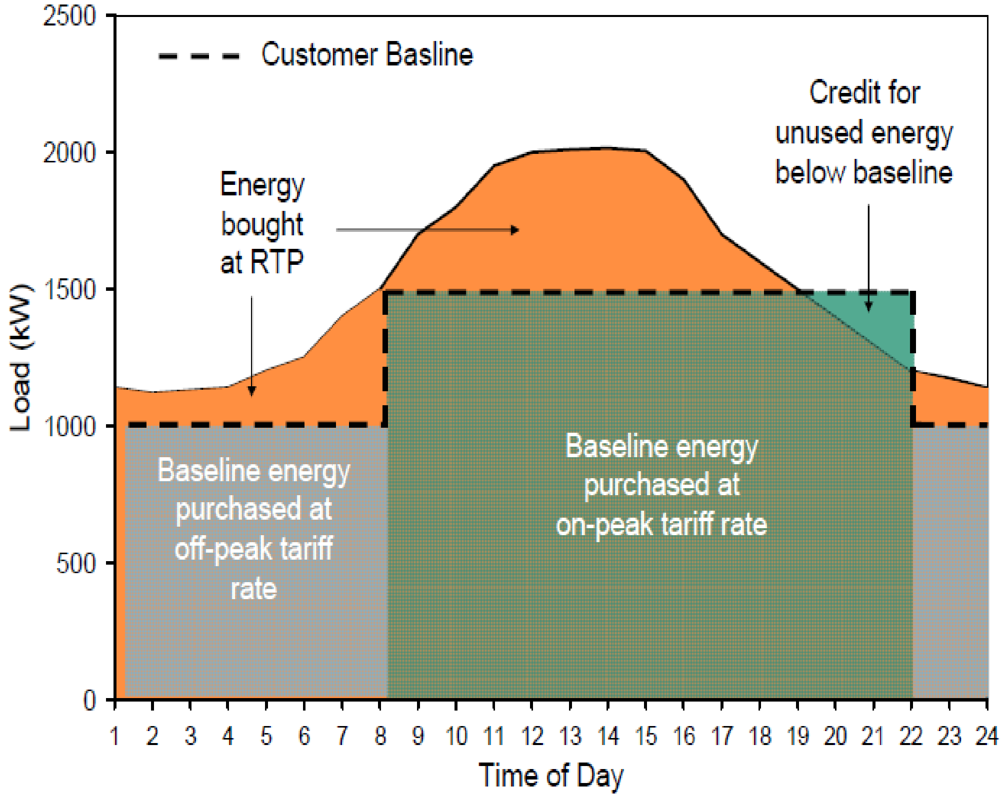

Figure 2-11: Operation of real-time pricing [60]

2.4.3.3 Interruptible/Curtailable Program

The I/C program has traditionally been one of the most common DSR models used by electric power utility companies. In this type of program, consumers sign an interruptible-load contract with the utility company to reduce their demand at a fixed time during the system's peak load period or at any time requested by the utility company [64]. This service provides incentives/rewards to consumers to participate to curtail electricity demand. The electricity provider sends directives to the consumers for following this program at certain times. The consumers must comply with those directives to curtail their electricity when notified from the utility company or face penalties [65]. For example, the consumers must curtail their electricity consumption starting from 18:00-19:00; those consumers who follow their direction will receive a financial bonus/reward in their electricity bill from the utility company. In California, the incentive of the I/C program was $700/MWh/month in 2001 [66].

2.4.3.4 Emergency Demand-Side Response Program

The EDRP is an energy-efficient program that provides incentives to consumers who can reduce electricity usage for a certain time; this is usually conducted at the time of limited availability of electricity. The EDRP provides participants with significant incentives to reduce load [67]. To participate in this program, all consumers are expected to reduce energy consumption during the events. The program determines which houses must be included in the event to minimise cost and disruption, while alleviating the overload conditions [68]. When asked to curtail, and when their participation has been verified, the consumer is paid as high as $500/MWh [69]. In New York, an emergency demand-side response program allowed participants to be paid for reducing energy consumption upon notice from the New York Independent System Operator (NYISO [70]).

Figure 2-12 indicates the importance of the EDRP during a reserve shortage that occurred in New York during July 2002. During this event, the NYISO was concerned about the high peak demands and real-time price spikes on July 29, 2002. Based on a forecast of similar or hotter weather on July 30, NYISO operated its EDRP and capacity program. The combined impacts of these two programs significantly reduced peak demand and reduced the real-time price on July 30.

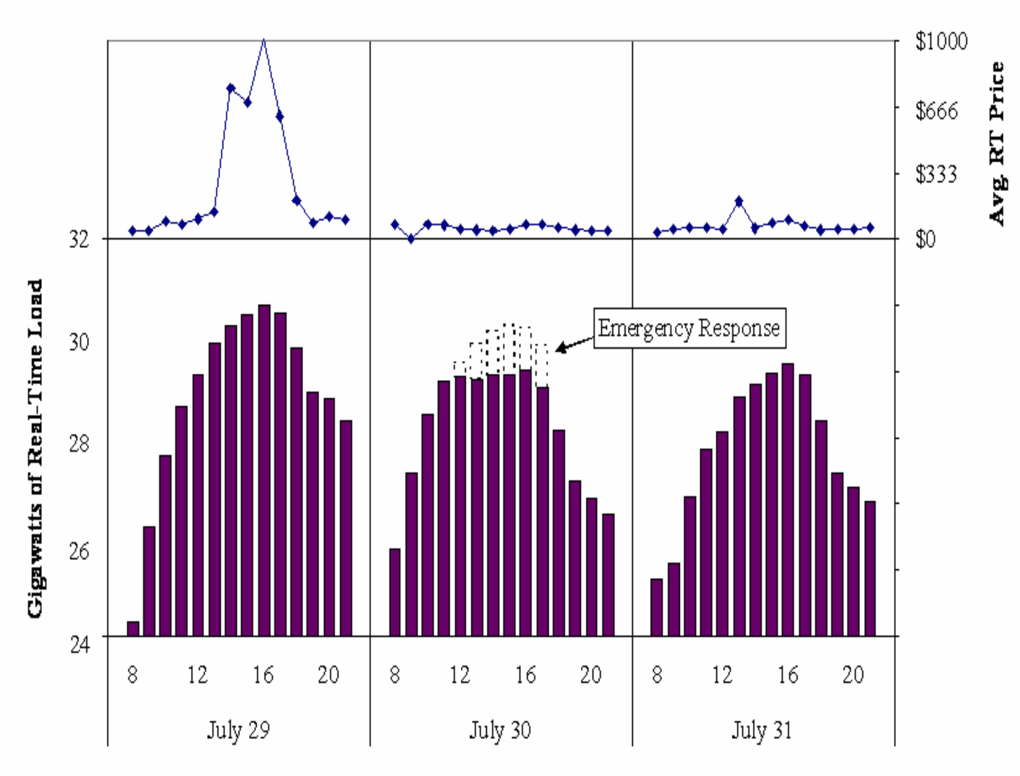

Figure 2-12: Impact of NYISO emergency demand-side response program [60]

2.4.4 Demand-Side Response and Air Conditioning

In managing the peak load contribution of air-conditioners in Australian homes and commercial premises, various strategies can be used. The issues considered important in the application of DSR in Australia are [71]:

1. Price Signal

   Residential and small commercial consumers generally purchase electricity on a uniform tariff, hence there is little incentive for the consumer to reduce or move the load at peak time. More cost-effective pricing would allow consumers to be more fully exposed to peak prices and give them sufficient financial or other incentives to reduce the load at particular times. A specific price signal for DSR can then be seen and the consumer can be rewarded for curtailing or eliminating peak loads, through payments for the reduced load and the ability to respond at peak times.

2. Metering and Signaling

The technical ability to participate must be present as well as the system to record and pay for the response. The widespread adoption of interval metres and/or signaling equipment for small consumers is required but costs and technical concerns have to be addressed. The appropriate choice of signaling method, direct control or manual is necessary in order to address the end-use load type and consumer type.

3. Suitable Load

   The control strategy for air-conditioning in residential and small commercial premises is still a barrier for many consumers. The overseas experience of millions of consumers in direct load control programs suggests that these barriers can be overcome.

4. Energy/Electricity Market Reform

   The spot market wholesale pricing system currently creates the incentive to offer capacity as the system pays all generators at the last highest bid price required to meet demand. This issue, combined with network companies being paid on the basis of capital investment, does not encourage DSR without a countervailing DSR system.

There are various ways to implement the DSR in the use of air-conditioning. The Markov birth and death process has been developed to manage small package air-conditioner loads based on a queuing system. This model enables residents with small air-conditioner loads to participate in various load management programs whereby they can receive incentives and lower their electricity bills while their conveniences are taken into account [72]. This model provides effective and convenient load management measures to both the power company and the consumer. Incentives and compensation are recognised by the utility company based on the level of participation of the consumers [72]. In this models, the electricity price was not based on the electricity market price. Therefore, the aggregator was not required to control small consumers. On the other hand, these models are not appropriate for anticipating a price spike and seasonal climate changes in Australia. As a result, these models were not considered as a pre-cooling method to avoid high costs.

A simple control strategy is also used to manage the air-conditioning in a DSR program in Kuwait. Due to the normal operation of air-conditioning in Kuwait on a 24 hour basis, the control system provides comfortable conditions during the occupancy period only. For example, the system is applied for five periods during a day: (i) 03:30-04:00, (ii) 12:00-13:00, (iii) 15:15-16:00, (iv) 18:00-18:30, and (v) 20:00-21:00. To achieve acceptable comfort conditions during these periods, a pre-cooling method is applied [73]. The pre-cooling method is applied by extending the operation time of the air-conditioning. The pre-cooling method is not based on the substantial risk of the price spike. Therefore, this method is not effective to be applied on the system if a price spike happens.

To increase the system reliability and to reduce the system operating cost, the direct control of air-conditioning load model is a common load management program to reduce peak loads. This is an effective tool for load scheduling, as it allows control periods of any length and any cycle rate to be applied [74, 75]. This process is appropriate for commercial buildings to use to minimise the demand so as to reduce consumer discomfort and maintain the generation of business incomes [76]. Customers can also participate in the direct load control program in the control centre of a micro grid to shift their air-conditioning demands through changing the ON and OFF cycle based on the real-time prices and weather conditions to save energy and to shift the system peak load [74]. This method is not applied as a pre-cooling method to anticipate a high price. Turning ON and OFF is used to control the AC status based on the real-time price and weather conditions from the utility. Therefore, the aggregator was not recognised to control the load of the AC for the small consumer.

With the development of demand-side management for future smart grid applications, residential loads are expected to provide an elastic response to fluctuating generation. The implementation of the demand-side response for the residential consumer involves the use of smart meters to control household appliances such as air-conditioning. The energy consumption scheduler provides information for the day-ahead load curve of the electricity price and temperature estimation [77]. The optimal scheduling using the best response technique can achieve the minimum energy cost. The energy consumption of each customer depends on the next day’s outdoor temperature profile and the energy usage of the other customers [77]. Communication between the consumers (smart meter) and the utility company is required in order to get information about the energy consumption schedule. The utility company is required to inform the day-ahead electricity price and outside temperature estimation for all consumers at all times. Therefore, the consumer can arrange the time to use the air-conditioning based on the signal from the utility company. To anticipate a high cost, a pre-cooling method is not applied on the system. On the other hand, the aggregator is not required in this model.

The Contingent Valuation Method has been developed to investigate the use of residential air-conditioning during the summer peak load [78]. In this method, two controlling periods are recognised, namely, the direct electricity interruption and setting the temperature with the minimum level. According to the controlling periods, there are four scenarios offered to the consumer: setting the temperature of the air-conditioner to no less than 28^{o}C for 30 minutes (scenario 1); setting the temperature of the air-conditioner to no less than 28^{o}C for 1 hour (scenario 2); interrupting the electrical power for 30 minutes (scenario 3); and interrupting the electrical power 1 hour (scenario 4). The results of a study into this method indicated that scenario 1 was the cheapest among the four scenarios [78]. This method was applied in China to minimise the energy cost for air-conditioning during the summer peak load. However, this method is not appropriate to meet a price spike in the electricity market where there is seasonal climate variation as in Australia. This method is not effective for consumers if they want to use the air-conditioning for different lengths of time.

Building operations can be a viable contribution for grid optimisation and reliability. The essential electric loads that allow for influence are heating, ventilation and air-conditioning (HVAC) [79]. The housing load is to be dominated by the power consumption of the HVAC. Demand-side response algorithms with large-scale and detailed grid simulations have been developed for the modelling of domestic housing. This model provides a fast and reliable simulation platform that can simulate and compare different energy management algorithms such as frequency-response algorithms and peak-demand reduction algorithms [80]. This model simulates the power consumption in an electric power grid. This model improves the computational building model to facilitate communication among buildings, offering reliability and availability. To set up the necessary remote instrumentation and control of the consumer, an electricity aggregator is required to participate to purchase the energy at wholesale price and resell it to the consumer, such as the EnerNOC in California [79]. This is similar to my model. However, the pre-cooling method is not applied on the system if there is a substantial risk of the price spike.

An equivalent thermal parameter (ETP) was developed in the residential air-conditioning model to forecast the room temperatures [81]. Forecasting of the room temperature is applied at the central controller to forecast thermostatically-controlled appliances such as air-conditioning. This model forecasts the room temperature by measurements obtained from the advanced metering infrastructure every several minutes (e.g., at intervals of 0.6 minutes). Advanced metering infrastructure is an emerging concept of the smart grid to improve DSM, increase energy efficiency, and allow a self-healing electrical grid [82]. The signal monitoring comes from the demand-side management of air-conditioning. The central controller controls the air-conditioning status (on or off) of each air-conditioning load while maintaining the desired ranges of temperature. The controllable and measurable load services that the controller provides can be used for many other demand-side response applications, such as peak shaving and load shifting [81]. The central control only communicated to the consumer regarding the weather conditions. The electricity price is not considered in arranging the AC status. Therefore, this model is not appropriate to meet a price spike in the electricity market. As a result, a pre-cooling method is not required to be applied on this system.

Considering the large family use of air-conditioning, the Monte Carlo model was developed to measure thermal resistance and capacitance corresponding to the ambient temperature [83]. In this model, the air-conditioning is switched on and off on a regular basis. The total demand of the system is initially constant. To examine the effect of the set point variation of temperature on the individual and aggregate dynamics of the air-conditioning load, the set point temperature is slowly raised by 0.1o C at a constant rate of 0.1o C/hour. This model is also used to account for the randomness of the thermostatically controlled load (TCL) parameters and initial temperature distributions of the air-conditioning [83]. This model is similar to the previously discussed method. The fluctuation of the wholesale electricity market price is not considered. Only seasonal climate change is considered to arrange the AC status. The aggregator is not required to control the small consumer.

Shifting the air-conditioning load of residential and commercial buildings from the peak season to the off-peak season under demand-side management control can thus be achieved if many buildings are equipped with such storage devices [84]. This method is used in Taiwan Power to anticipate the peak in summer. The load demand is used for more than 50% of air-conditioning in the summer season [84]. The mathematical modelling is proposed for an air-conditioning system with a chilled water storage tank. The proportional integral (PI) system controller senses the temperature deviation through the temperature sensor on the fan coil unit and actuates the valve to control the flow rate of the chilled water [84]. Based on the results of an investigation into this method, the analysis indicated that the designed PI controller was very effective in controlling the indoor temperature of the building [84]. Through the installation of the storage tank, more than $3000 of savings in electricity fares could be achieved since the air-conditioning load was shifted from the daytime to the evening discount period [84]. This model is applied to anticipate a high cost in the summer season, which is similar to my model. However, this model only controls the AC status based on the temperature change. The electricity market price spike is not considered to determine the AC status. On the other hand, the aggregator is not required in the system. In the peak season, the consumer was expected to participate in this system by shifting the AC load to the off-peak season or use the storage devices.

The process for the consumer to minimize energy while keeping comfort within specification is to control each switching instant of the AC. When the total cost is minimized then in many cases where price risk is low it is appropriate to make no special preparation. However when the price risk is high the optimal switching pattern makes use of pre-cooling. At the level of optimization with constraints no other outcome is feasible. Other methods of cost reduction are examined above but none of these had the potential for the same level of savings found in this thesis.

2.5 CONCLUSION

In this chapter, an overview of electricity price and demand, price spikes in the electricity market and smart grid DSR programs has been presented. A review of the literature revealed that a wide range of efforts has been undertaken to alleviate peak demands by using DSR programs. In this research develops a model is used by consumers to mitigate the peak demand based on the electricity price signal. The price signal is based on the electricity market price issue and feeder over-loading.

As discussed in Section 2.2, the fluctuation of electricity market price is based on the electricity demand. Therefore, the characteristic of the electricity market price is that it is similar to the pattern of electricity demand. However, a price spike in the electricity market may occur any time during a day. As discussed, the weight of the network cost is around 45 per cent of the total retail price. As a result, this cost is one of a number of factors that contribute to increases in the electricity price. In addition, it is noted that climate change has a significant impact on the electricity demand on summer days, because of high temperatures and the increased use of air-conditioning.

As discussed in Section 2.3, the meaning and definitions of electricity price spikes are provided in the literature. In this thesis, the definition of a price spike is based on the experienced probabilistic distribution in a specific period; in this case, on week days during hot summer days from 2011 to 2012, as discussed later in Chapter 4 (Section 4.4).

In Section 2.4 a review of the smart grid demand-side response model is presented, including an overview of DSR models, the benefits of DSR, categories of DSR and the application of DSR models in Australia and other countries As well as implementing DSR program to the air conditioning. In this thesis, a DSR program is applied to the use of air-conditioning in order to assist consumers to mitigate the peak impact on the electrical system, as described in Chapters 5 to 8.

Chapter 3: Application of the Market Price to Small-Consumers: the Aggregator

3.1 INTRODUCTION

This chapter outlines the application of market price to small consumer to expose some portion of their load to electricity market price and network congestion charges. Section 3.2 discusses the meaning of aggregator; section 3.3 summarises the aggregator and small consumer; section 3.4 discuss the proposed model of aggregator; section 3.5 conclusion.

3.2 MEANING OF AGGREGATOR

Demand side response systems, which can vary both the supply and consumption of electricity, lack effective and well-understood pricing mechanisms to incentivize user participation [85]. Recently, a new promising business model, 3rd party demand response aggregator has emerged as a way to resolve the disparity in benefits between utility and consumer side. A demand side response aggregator acts as a broker between a market operator or electricity supplier and small customers within a group to generate desirable demand response for market operator or electricity supplier by aggregating potential energy cutbacks from a group of consumers. In such a business model, the market operator or electricity supplier can reward demand response activities not only for energy saving, but also for capacity reduction, which is able to be translated into a new power plant reserve [85] .

An aggregator is a broker or third party that acts on behalf of number of small-consumers (this is termed a group). The existence of aggregators allow negotiation of electricity price with an electricity supplier or market operator located within their corporate borders or their group. Aggregators are entities that gather potential customers together to be served by a competitive electricity supplier [85]. An Aggregator joins two or more customers into a single purchasing unit to negotiate the purchase of electricity from Retail Electric Providers (REPs) extend to the network as well [86]. An aggregator is any organisation or individual that brings retail energy consumers together as a group with the objective of obtaining better prices, services, or other benefits when acquiring energy or related services [87].

Electric load aggregation is the process by which individual consumer are brought together in an alliance to secure more competitive prices [88]. An Aggregator represents a group of customers who have banded together perhaps through their neighbourhood association e.g. houses in the same street or suburb. Aggregators may recruit members from anywhere there is electricity choice. For the entrepreneur, aggregation is a new business opportunity in a competitive electric market. By managing groups of consumer and their electricity loads, Aggregators can provide a valuable service [86].

3.3 ROLE OF AGGREGATOR AND THE SMALL CONSUMERS

To implement DSR program, consumer is required to enrol as a member of a group controlled by an aggregator. To be exposed to electricity market price and network overload costs, small-consumers need an aggregator to communicate and negotiate the electricity market price and network overload. Any change in the electricity usage for the small-consumer is based on the information from the aggregator. As a result, aggregators keep and maintain communication between market operator and consumers.

Based on the regulation of electricity market, small consumer is not allowed direct participation to the wholesale electricity market. Under such a mechanism, only large consumers can offer to curtail or shifting a proportion of their load or bid to wholesale electricity market price and demand. The small-consumer is only able to register in the electricity market through the aggregator. This is envisaged that this mechanism could be rolled out to smaller consumers.

In the competitive electricity market structure, the aggregator concept describes an independent agent providing its small-consumers with a wide range of innovative services including bill management, home management, home electricity generation, and other services [89, 90]. Based on these service provisions, the aggregator combines its consumers into a single purchasing unit to negotiate the purchase of electricity from the retailer [89]. The aggregator also negotiates demand response and behalf of the consumer with the retailer, distribution and transmission company. Many economists believe that the participation of aggregator with innovative services and consumer aggregations can offer potential solutions for small-scale consumers to effectively manage their consumption, and thereby becoming active participants in the electricity market [87, 89-91]. The aggregation methods, the combining multiple electricity load, provides the benefits of retail electric competition for the consumer with lower electric usage called a small consumer.

The following Figure 3-1 indicates the competition of power structure in the electrical system. Aggregator is a third party is allow to negotiate of electricity market direct to the market operator and transmission company. The physical electricity flows delivery from generator by transmission and distribution companies to the consumer. In contrast, the financial electricity flow delivery from consumer through Retailer Company to the market operator then continues to generator. In the competitive electricity market structure, aggregator is needed to do coordination with the retailer and distribution company to provide good service to the consumer. These service include the information about electricity market price and demand. As a result, small-consumer can participate to the wholesale electricity market.

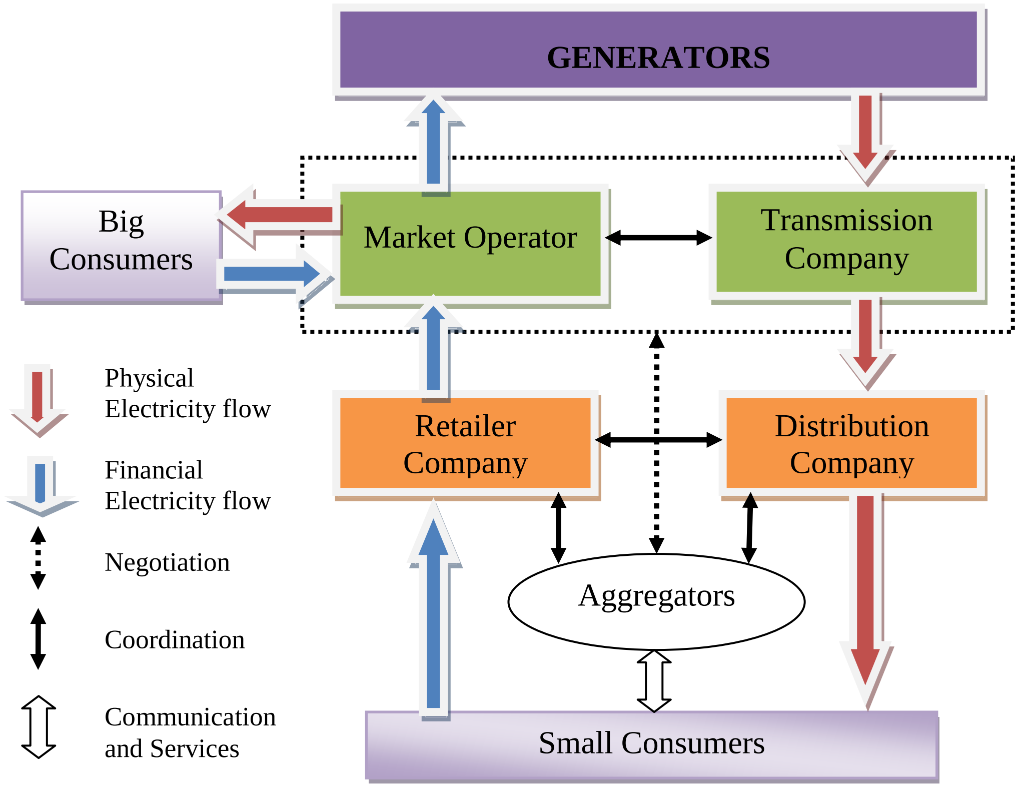

Figure 3-1: Competition in the power system structure

The membership composition of aggregator can be a loosely defined group based on the geographical area, institutional consumer e.g. school or university, small-industrial consumer, farm consumer, etc. Each group has unique advantages or disadvantages. However, the benefit for aggregation model is the opportunity for small consumer (called residents) and small businesses to save money on their electric bills by exposure to the electricity market. If the electrical power is supplied from a renewable energy source, there are also opportunities for helping the environment as the group could purchased 100% renewable energy for its electric aggregation program. Another benefit is that by negotiating on behalf of all residents and small businesses, the aggregator can obtain favourable contract provisions.

3.4 THE PROPOSED MODEL OF AGGREGATOR

In this research, to participate in DSR program every consumer can be at least partly exposed to the electricity market through an aggregator. The consumer can minimise the energy cost for the air conditioning by controlling temperature. In this case, aggregators need to work very closely with consumers to look at their overall energy consumption and load shape, help them understand how much load can be dropped and at what times. Curtailment plans are thus tailored to aggregator who is financially rewarded for both the commitment to dropping load, and actual load curtailment as well as when consumer applying pre-cooling method. The level of payment may also depend on the frequency and length of the DSR period.

The following Figure 3-2 indicate the aggregated DSR program. All parties see impacts from demand response in near real time. Market operator initiates a request for a DSR program. Communication system alerts third party aggregator to request consumer to apply DSR program. Consumer or their authorized appliances receive a message from aggregators to implement the DSR program. If the consumers optimise the air conditioning then a potential of collective benefits exist. The benefit sharing arrangement is according to the agreement. The consumer earns revenue because of their participation in DSR program. The aggregator obtains benefit because of the management control of market for the group consumers.

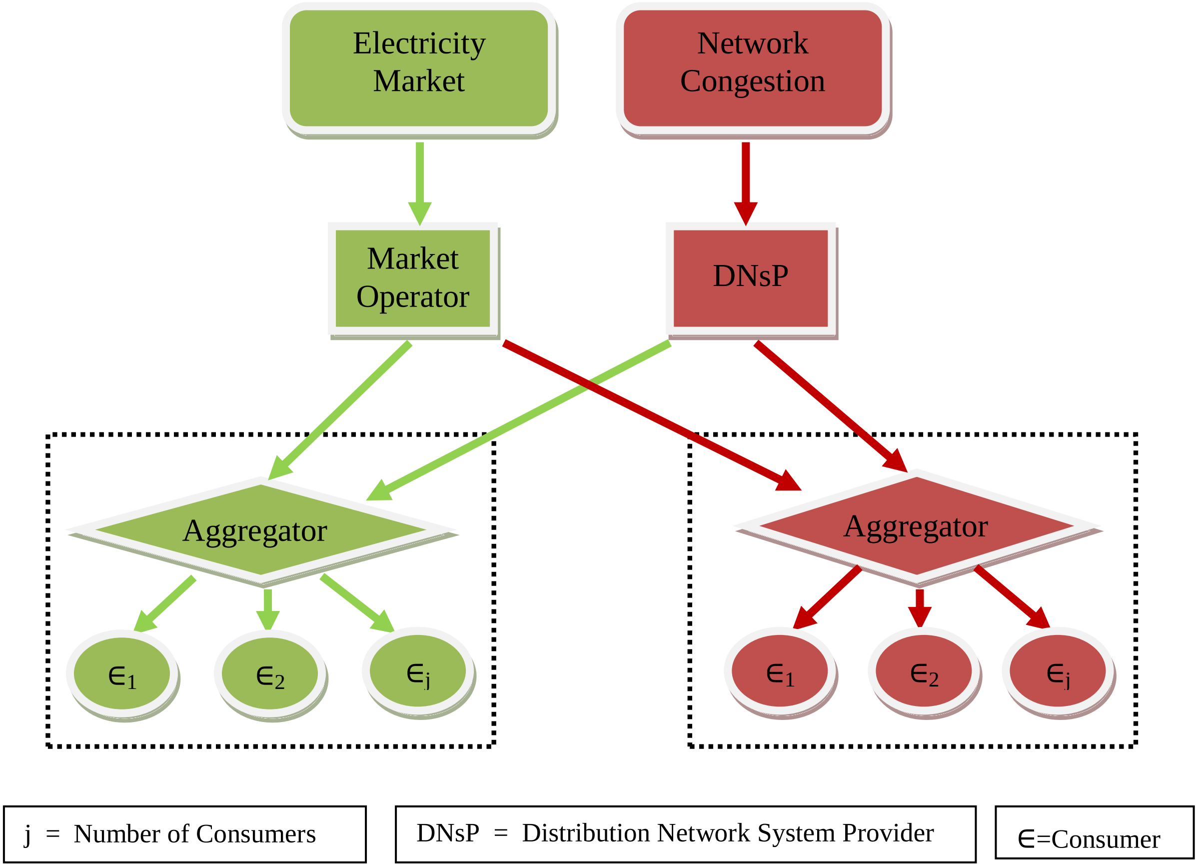

Figure 3-2: Aggregator model structure

Under a full-requirements DSR contract, the consumer must optimise the temperature to anticipate a price spike of electricity. As a result the consumer and aggregators can earn revenue. The collective benefit for them is obtained by minimising energy cost through DSR program. The collective benefit for the aggregator and consumer is obtained by the different cost spent by consumer with and without the DSR program. In addition, the consumer may anticipate if feeder over load may occur during a day. Under a full-requirements contract, the consumer typically pays for a greater proportion of high-cost power regardless of when the energy is consumed. Through supply portfolio structuring, the consumers can lower energy costs by optimise their air conditioning under a DSR program. Similar to the previously method, the collective benefit can still exist for both consumer and aggregator.

3.5 CONCLUSION

In this chapter, a brief review of aggregator is presented. In our opinion, aggregator is required for the consumer to apply DSR program. Small-consumer exposed electricity market trough an aggregator.

In section 3.2 reviewed of the meaning of aggregator is presented. An aggregator is a third party operating on behalf of small consumer to allow negotiations with the electricity market direct to the market operator located within their corporate borders or their group. In DSR program, aggregator acts as a broker between a market operator or electricity supplier and small customers within to generate desirable demand response for market operator or electricity supplier by aggregating potential energy cutbacks from several numbers of consumers. Therefore, the aggregator should be keep and maintain good communication between consumer and market operator.

In section 3.3 a review of aggregator and small consumer relation possibilities is presented. To participate directly with the wholesale electricity market, small consumer can be partly exposed to the electricity market by the aggregator. Any change in the electricity usage for the small-consumer is based on the information from the aggregator. The aggregation method is provide benefit for the small consumer e.g. to save money on their electric bills. The composition of the member of an aggregator can be based on the geographical area e.g. street or suburb, institutional consumer e.g. school or university, small- industrial consumer, farm consumer.

Section 3.4 reviewed the proposed model of the aggregator. In participation in DSR program, a communication system between aggregator and consumer is required. Consumer receive a message from aggregators to implement the DSR program. If the consumers optimise their air conditioning, then a potential of collective benefits exist. The benefit sharing arrangement is according to the agreement between consumer and aggregator. The collective benefit for the aggregator and consumer is obtained by the different cost spent by consumer with and without the DSR program.

Chapter 4: Basic Methodology

4.1 INTRODUCTION

This chapter outlines the proposed methodology which can be used by consumers to mitigate the peak demand of air-conditioning based on the electricity market price and network demand. This chapter describes the design adopted in this research to achieve the aims and objectives stated in Chapter 1 (Section 1.3). Section 4.2 discusses the numerical optimisation used in the study; Section 4.3 summarises the typical room and air-conditioning used in this analysis; and Section 4.4 discusses the data processing and analysis.

4.2 NUMERICAL OPTIMISATION

The proposed model summarises a DSR which assists electricity consumers to be engaged in mitigating the air-conditioning price and load peak impact on the electricity system. The model allows consumers to independently and proactively manage air-conditioning peak electricity demand. This research investigated how consumers can optimise energy use to operate air-conditioning considering particular cases in the market price domain, namely, spike case and the probable spike case.

Numerical modelling is a feasible solution to allow for unpredictable market price changes due to the interruption of major generation or other supply-side constraints. To conduct this investigation, mathematical models for the consumer participant were developed to quantify the economic effect of demand-side variation. A linear programming-based algorithm was developed to determine the optimal solution to achieve the best outcomes. In addition, the developed model was designed to be applicable for load demand constraints to give good economic performance for electricity generation, transmission and distribution.

The model shows how air-conditioning should decrease temperature loads in high temperature periods when there is a substantial risk of a price spike, that is, by applying a pre-cooling method to avoid high prices in a critical peak period.

Consumers are able to operate the air-conditioning usage by controlling the desired levels of room temperature, turning on the air-conditioning when the temperature rises to a maximum threshold (i.e., 25^{o}C) then turning it off for the next period until the temperature drops to the minimum threshold (i.e., 19^{o}C). In addition, this research investigated how consumers can optimise energy costs when they have not committed to the permitted temperature. On this optimisation process, when the room temperature is less or more than the minimum or maximum temperature threshold then a penalty to the optimization process will be identified. The cycling time of the air-conditioning is based on the result of temperature optimisation.

In this research, a pre-cooling method was examined as a way to minimise energy costs. Pre-cooling is a method to reduce the room temperature in advance of a possible spike. This method is considered to be effective because it can minimise energy costs and can keep room temperatures comfortable for the consumer. However, pre-cooling is only undertaken when there is a substantial risk of a price spike because it costs a lot and the spike may not always occur on the system. However, while applying this method is expensive, it is more efficient than switching on the air-conditioning at all times during the critical time [92].

The objective is to minimise energy costs by optimising room temperatures. The energy cost is based on the air-conditioning status, that is, no cost when the air-conditioning status is off ($\mathrm{U_t} = 0$) and market cost if the air-conditioning status is on ($\mathrm{U_t} = 1$). To achieve this objective, an optimisation package such as MATLAB allows the user to carry out optimisation within operational constraints such as a permitted temperature range.

In the optimisation process, the MATLAB optimisation toolbox function *fmincon* and the ordinary differential equation solver ODE45 were used. The toolbox functions of *fmincon* were applied using the default option to be acceptable in this work. The *fmincon* was used to determine the optimal parameter of the ordinary differential equation. The ODE45 is used to solve the initial value of problems involving an ordinary differential equation. The ODE45 is more complicated and will take longer steps. However, the accuracy of the result obtained in this study was higher than the accuracy of the result using the ODE23. That made the ODE45 more favourable and reliable than the ODE23 [93].

In order to formulate the participation of the consumer in the DSR program, the energy cost model which represents the changing temperature and electricity price was developed as reported here. The optimisation problem can then be represented as minimised energy cost (Z), or mathematically:

$$Z(t) = \int_{t=1}^{t=n} [(C(t)\ dt \tag{4.1}$$

$$Z(t) = \int_{t=1}^{t=n} [(S(t) \, . \, P(t). D(t). U(t))\ dt\,] \tag{4.2}$$

Subject to constraints [92, 94]:

$$\frac{dT}{dt} = \frac{Q.\ A\,.\ (T_0(t) - T(t)\,)}{H} - \frac{B.U(t)}{H} \tag{4.3}$$

Where:

Z = Minimised energy cost (A$)

C = Cost ($)

S = Electricity price (A$/kWh)

P = Rating power of air conditioning (kW)

D = Duration time (hours)

U = Continuous time binary variable (1 or 0)

Q = Heat transfer coefficient from floor walls and ceiling (W/m^2 ^{o}C)

B = Heat transmission from the air conditioning (W)

A = Total area (m^2)

H = Heat capacity of the room (J/ ^{o}C)

T_o = Temperature outside (^oC)

T = Temperature inside the room at time t (^oC)

During the optimization if the room temperature is more or less than the maximum or minimum temperature ($Tmax\ or\ Tmin$) threshold, the minimization will add a penalty to the computed cost. The penalty will be calculated as follows:

$$\text{If } \mathrm{T(t)} > Tmax \text{ Then Penalty} = \mathrm{K} \tag{4.4}$$

$$\text{If } \mathrm{T(t)} < Tmin \text{ Then Penalty} = \mathrm{K} \tag{4.5}$$

$$\text{Else Penalty} = 0 \tag{4.6}$$

Therefore, the energy cost will be calculated by:

$$\mathrm{Z(t)} = \int_{t=1}^{t=n} [\mathrm{C(t)}\ \ \mathrm{dt}] + \mathrm{K} \tag{4.7}$$

$$\mathrm{Z(t)} = \int_{t=1}^{t=n} [(\mathrm{S(t)} . \mathrm{P(t)}. \mathrm{D(t)}. \mathrm{U(t)})\ \ \mathrm{dt}] + \mathrm{K} \tag{4.8}$$

4.3 TYPICAL ROOM AND AIR-CONDITIONING

Table 4-1 summarises the parameters of an example room and air-conditioning used in this analysis.

Table 4-1: Parameters of the example room used in this analysis

No.	Parameter	Value	Unit
1	Heat transfer coefficient from floor wall and ceiling (Q)	1	W/m2 ^{o}C
2	Total area (A)	54	m2
3	Heat capacity of the room (H)	48	J/ ^{o}C
4	Heat transfer from the air conditioning (B)	900	W
5	Reference of temperature	22	^{o}C
6	Hysteresis	3	^{o}C
7	Maximum temperature	25	^{o}C
8	Minimum temperature	19	^{o}C
9	Rating power of air conditioning (P)	2.6	kW

4.4 DATA PROCESSING

4.4.1 Price Spike in the Electricity Market

The cumulative probability distribution of the Queensland electricity market price data from the AEMO from 2011 to 2012 on hot days is used to determine a price spike on different types of days in different price ranges as given in Table 4-2.

Table 4-2: Cumulative probability distribution of the Queensland electricity market price during hot days in 2011 to 2012

Range RRP (A$/MWh)	Weekday		Weekend		All day	
	Frequency	Prob of occurence	Frequency	Prob of occurence	Frequency	Prob of occurence
<=50	2627	72.97%	1140	76.61%	3767	74.04%
50-75	608	16.89%	279	18.75%	887	17.43%
75-100	116	3.22%	39	2.62%	155	3.05%
100-150	76	2.11%	11	0.74%	87	1.71%
150-200	43	1.19%	11	0.74%	54	1.06%
200-500	99	2.75%	8	0.54%	107	2.10%
500-2000	11	0.31%	0	0.00%	11	0.22%
>2000	20	0.56%	0	0.00%	20	0.39%
Total	3600	100%	1488	100%	5088	100%

In the present research, after analysis of the historical data, a threshold value of A$75 per MWh was used for analysis of the Queensland electricity market during weekday periods. This means any regional reference price more than A$75 per MWh is called a price spike. The average of the electricity prices under A$75 per MWh is called the non-spike price, which in this period was A$30.69 per MWh. Figure 4-1 indicates the RRP of the electricity market in Queensland during hot days in 2011-2012. The data presented in the table shows clearly that any price above the red line is a so-called price spike.

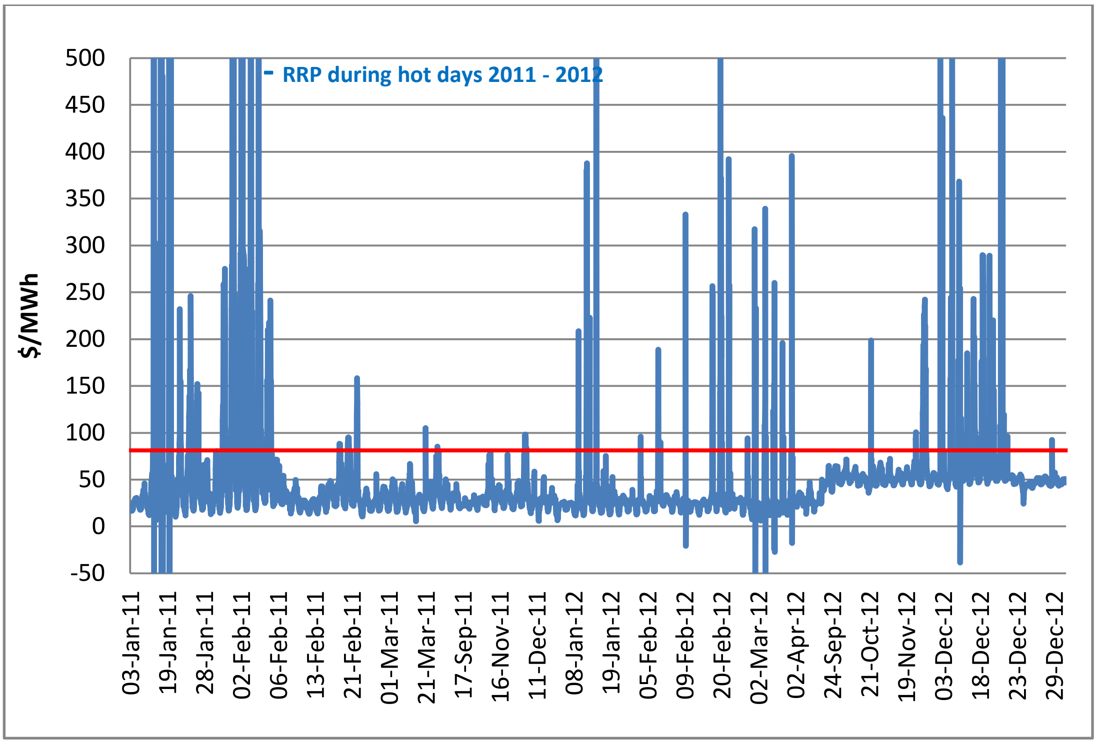

Figure 4-1: Electricity market price in Queensland during hot days in 2011-2012 [4]

4.4.2 Expected Value of A Price Spike

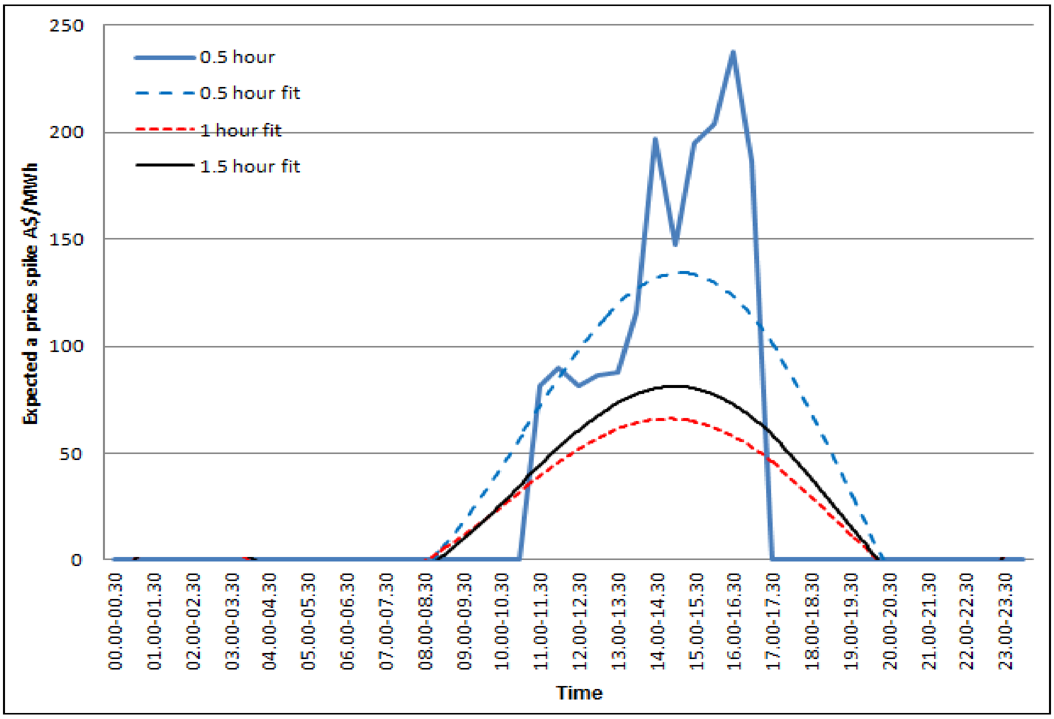

Figure 4-2: Expected value of a price spike during hot days in 2011-2012 [4]

Figure 4-2 illustrates the expected value of a price spike for a half hour spike, one hour spike and one and a half hour spike. The characteristics of the expected values were similar to the pattern of the outside temperature. The expected value of a price spike was increased starting from 10:00 when the outside temperature increased. In contrast, the expected value was decreased to a low level when the outside temperature decreased. This indicated that the outside temperature has a significant impact on defining the price spike during a day.

4.4.3 Hot Days and Outside Temperature

In this research, any day on which the average daily temperature was more than 30^{o}C is called a hot day, as given in Figure 4-3. In addition, the temperature data on 29 February 2012 was selected for the outside temperature (To), as given in Figure 4-4. Figure 4-4 summarises an example of classic fluctuations in outside temperatures in Brisbane. The temperature is typically at its lowest level during the morning and at night time. Normally, the daily outside temperature increases in the middle of the day.

In the example, the highest temperature occurred from around 12:00 to 17:00. The outside temperature around these times was more than 30°C. The maximum temperature of 35°C occurred at 15:00. The minimum temperature of 18°C occurred in the early morning (05:00 to 05:45). The average temperature was 25°C.

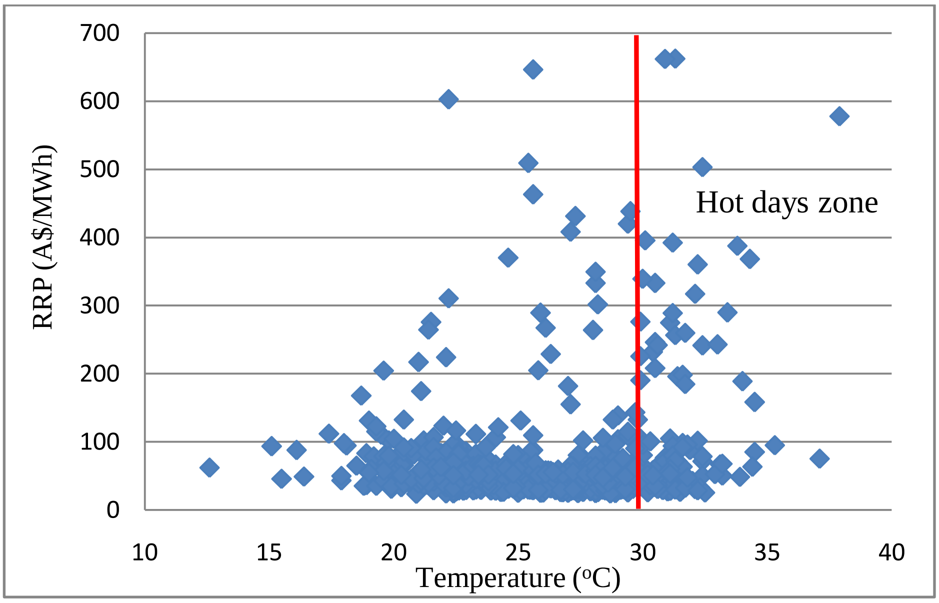

Figure 4-3: Classification of hot days, 2011 to 2012

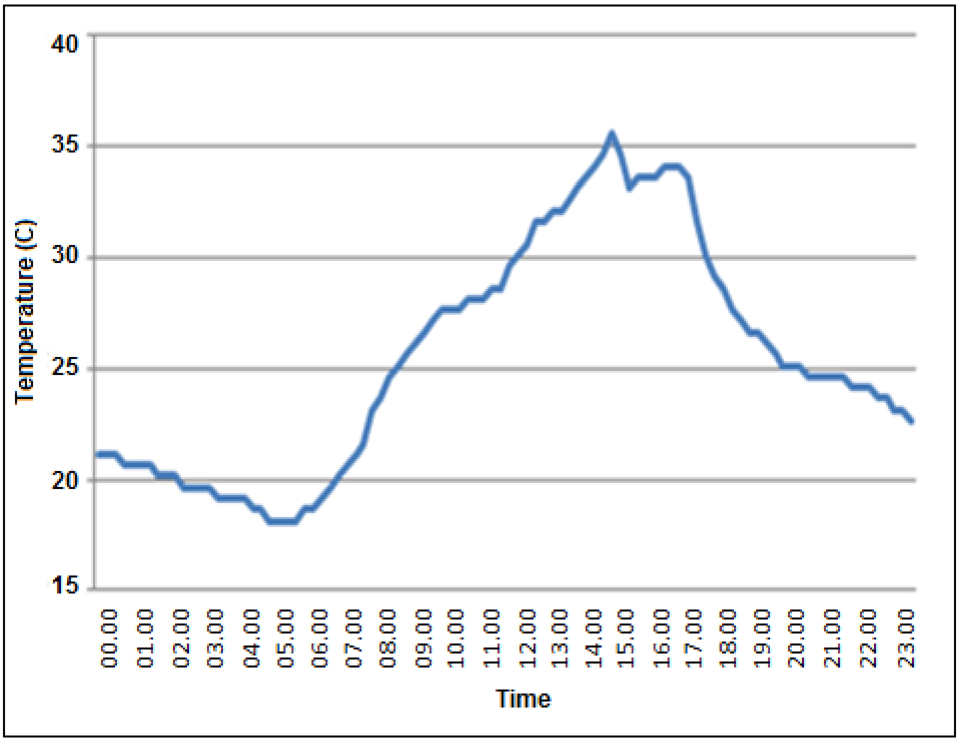

Figure 4-4: Brisbane outside temperature (To) on 29 February 2012

4.4.4 Probability of a Price Spike in the Electricity Market

In an ideal competitive electricity market, a price spike only happens when the demand exceeds supply. In reality, most electricity markets are not ideal competitive markets; consequently, price spikes occur even when there is sufficient supply to meet the demand [20]. Based on the general analysis, considering the situation of the Queensland electricity market, the probability of a price spike has a close relationship with demand, reserve and time. It can be summarised as follows [20]:

1. The probability of a price spike is high when the demand is high; otherwise, it is low.
2. The spike probability is high when the generation reserve is smaller than a certain level; the reserve level has a closer relationship to price spikes.
3. Price spike probability is higher at daily peak hours and is lower otherwise.
4. Price spike probability is higher on working days than on weekends and public holidays.

In the historical electricity market data where there are spike events, the probability of an event spike is shown in the equation below [95]:

$$P_D(t) == \frac{\text{The number Spikes at a given duration spike of the day } (t)}{\text{The total number of hours}} \quad (4.9)$$

Equation (4.9) is used to compute the probability of an electricity price spike for every hour of the day during a weekday period considering only hot days is as shown in Figure 4-5 below. The probability of spike with durations of half hour, one and one and half hours are separated. Based on the spike time duration, there were several cases of a price spike during hot days in 2011 – 2012. In this research we only considered some cases (i.e. half hour, one hour, and one and a half hour spike) for analysis. A price spike case of two hours or more was not considered because the probability of a price spike more than 1.5 hours was very small.

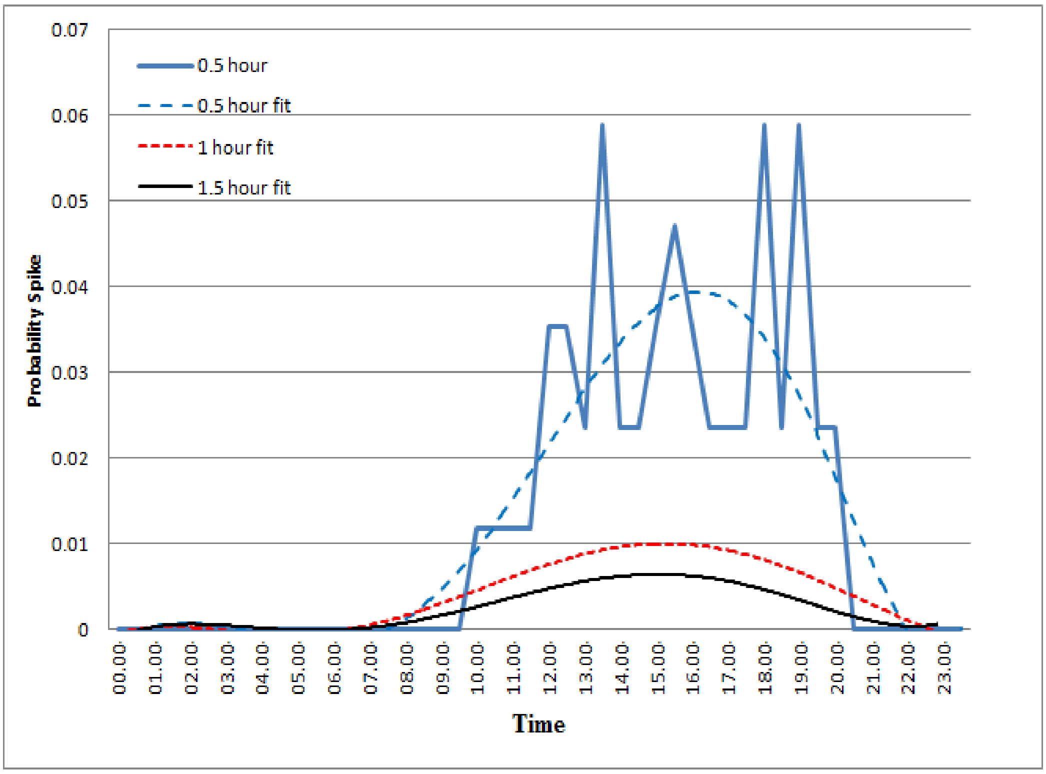

Figure 4-5: Probability of an electricity price spike in Queensland vs. time on a weekday during hot days, 2011-2012

4.5 CONCLUSION

This chapter has introduced and discussed the basic of methodology for this research. The numerical optimisation is used to determine the optimal solution to minimise the energy cost for the air-conditioning. The mathematical modelling has been developed to identify the energy cost for the air conditioning which can be used by the consumer. A pre-cooling method was discussed to avoid expensive cost if there is a substantial risk of the electricity market price and network overload.

This chapter has illustrated the parameters of typical room and the air conditioning is used in this analysis. This also investigated the data processing of the electricity market price, identified the hot days categories and outside temperature. In addition, the probability of electricity market price spike was identified based on the historical electricity market data from AEMO.

Chapter 5: Case of Optimise Energy Cost for the Air Conditioning if a Price Spike May Only Occur at Mid Day

5.1 INTRODUCTION

This chapter describes DSR model used by consumer/aggregator to minimise energy costs for the air-conditioning if a market price spike in the electricity market can only occur exactly in the middle of the day. First, the methodology for this case study is described, followed by a description of the pattern of operation of air-conditioning without the DSR program. Next, the application of the DSR program as the optimal solution for the energy costs if a spike may only occur in the middle of the day is described. The optimal solution for the energy costs if a spike may only occur in the middle of the day is then assessed, considering the probability of a spike. The benefits of the DSR program are also identified.

5.2 DESCRIPTION OF METHODOLOGY FOR CASE STUDY 1 – MID DAY SPIKE TIME MARKET ONLY

Consumers should start to apply the DSR program to optimise the air conditioning as soon as they receive information from the aggregator. Due to the pattern of high outside temperature, the consumer is required to participate in the DSR program starting from 10:00 to 19:00. The case study reported in this chapter illustrates the optimisation of the air conditioning if a spike may only occur at midday as well as related to the spike probability. This model is only appropriate when we know the spike may only occur in the middle of the day.

Numerical modelling is a possible solution to minimise the energy cost by control the room temperature with consideration of the varying electricity market prices and outside temperatures. In this simulation, the maximum and minimum permitted temperatures of 25^{o}C and 19^{o}C were chosen. There are 20 switch edges characterizing the switching decisions, from this we can compute the energy cost for the air conditioning. The numerical minimization was applied to find to set of edges which satisfy the constraints and provide minimum cost. The process is required to do optimisation of the cost.

The energy cost was calculated when the air conditioning was on, and the cost was zero when the air conditioning was off. This method continued until the time of operating the air conditioning had expired. To make the temperature comfortable for the consumer, the room temperature was only allowed to be between 19^{o}C and 25^{o}C. This means the temperature was not allowed to reach the maximum and minimum permitted temperatures. For the purpose of the simulation, the starting point temperature of 22^{o}C was chosen with the air conditioning status off. Table 5-1 summarises the parameters of the typical room and the air conditioning used in this optimisation.

Table 5-1: Parameters of the example room used in this analysis

No.	Parameter	Value	Unit
1	Heat transfer coefficient from floor wall and ceiling (Q)	1	W/m^{2} ^{o}C
2	Total area (A)	54	m^{2}
3	Heat capacity of the room (H)	48	J/ ^{o}C
4	Heat transfer from the air conditioning (B)	900	W
5	Reference of temperature	22	^{o}C
6	Hysteresis	3	^{o}C
7	Maximum temperature	25	^{o}C
8	Minimum temperature	19	^{o}C
9	Rating power of air conditioning (P)	2.6	kW
10	Number of switch change events	20	

Applying the pre-cooling method was needed to anticipate the expensive cost when a price spike may occur in the middle of the day. This method was applied for 3 directions of price spike (e.g., half hour, one hour, and one and a half hour). It was also applied by considering the probability of such a price spike. This method should be applied if there is a substantial risk of a price spike.

5.3 COST AS A FUNCTION OF A PRICE SPIKE WITHOUT DSR PROGRAM

The aim of the controller is to maintain the temperature of the room between some lower and upper temperatures in order to keep it within comfortable limits. For this simulation, the starting point of 22°C was chosen with the air conditioning status off. The lower and upper temperatures were 22°C to 24°C. The air conditioning was turned on once the temperature rose to the selected maximum. Next, the air conditioning was turned off once the temperature dropped to the selected minimum. With the air conditioning off, the temperature could increase and rise to the selected maximum. The typical operation of the air conditioning is continuous without control by the DSR program. To operate the air conditioning in this case, the consumer did not consider a price spike. On the other hand, due to the outside temperature, a price spike in the electricity market may occur in one hour, half hour, and one and a half hour spikes. Figure 5-1 illustrates the cycling temperature and the market cost if a spike may occur in the middle of the day.

In this simulation, there are 20 switch edges to compute the energy cost for the air conditioning. If S_s is the electricity price when a spike occurs, C_s is the market cost for spike cases, and K is the penalty, then the total market cost for the spike case ($MC_{1,2,3}$) is determined by the following equation:

$$MC_{1,2,3}(t) = \int_{t=1}^{t=n} [\, C_s(t) \;\; dt \,] + K \tag{5.1}$$

$$MC_{1,2,3}(t) = \int_{t=1}^{t=n} [(\, S_s(t)\, .\, P(t).\, D(t).\, U(t)) \;\; dt \,] \; + K \tag{5.2}$$

Equations (4.3) to (4.6) and (5.1) and (5.2) were used to compute the results of simulation without DSR program when a half hour spike one hour spike and one and half hour spike may occur in the middle of the day, as shown in Figure 5-1.

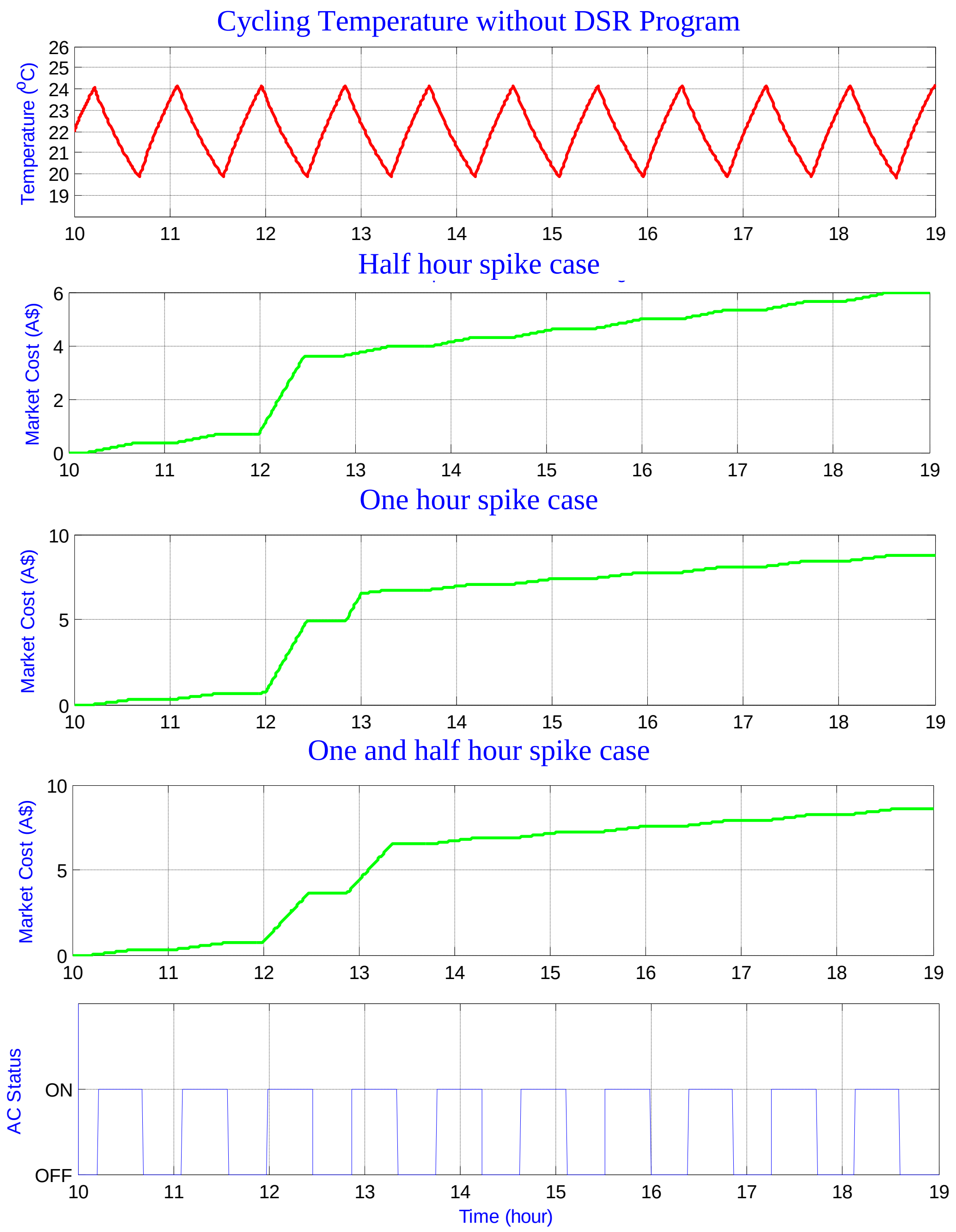

Figure 5-1: Cycling temperature and market cost without DSR

As shown in Figure 5-1, the calculation of the electricity cost during this period was based on the air conditioning status. The electricity cost increased when the temperature was being reduced by having the air conditioning on. However, there was no electricity cost when the air conditioning was off or electricity costs were not calculated when the air conditioning was off. The electricity cost calculation started from switch number 1 to number 2. Then, the air-conditioning was turned off again between switch numbers 2 to 3, when the electricity cost is zero. The type of operation was continuous for all switching and all times. The consumer/aggregator pays the cost according to the normal price before and after a spike happens. The price spike was only calculated when the spike happened in the middle of the day. In this case, three kinds of spike were considered, namely, the half hour, one hour, and one and a half hour spike. The electricity market cost of the one hour spike was higher than the others. This was because of the nominal price of the spike and duration of the spike. If a half hour spike (MC_1), one hour spike (MC_2) and one and a half hour spike (MC_3) are defined for the total market cost under the DSR program, then the total market costs of every spike are as presented in Table 5-3.

Table 5-2: Cycling temperature without DSR program

Switch Number	Time to Switch On/Off	AC Status	Switch Number	Time to Switch On/Off	AC Status
1	10:13	ON	11	14:38	ON
2	10:41	OFF	12	15:07	OFF
3	11:05	ON	13	15:31	ON
4	11:34	OFF	14	15:59	OFF
5	11:34	ON	15	16:23	ON
6	12:28	OFF	16	16:52	OFF
7	12:28	ON	17	17:15	ON
8	13:21	OFF	18	17:43	OFF
9	13:45	ON	19	18:07	ON
10	14:14	OFF	20	18:36	OFF

Table 5-3: Total market cost without DSR program

	Half Hour Spike (MC_1)	**One Hour Spike (MC_2)**	**One and Half Hour Spike (MC_3)**
Total Market Cost (A$)	5.99	8.79	8.57

5.4 COST AS A FUNCTION OF A PRICE SPIKE UNDER DSR PROGRAM

The control system optimised the room temperature of the air conditioning to define the energy cost for consumers. The aim of the controller is to maintain the temperature between the permitted maximum and minimum temperatures in order to provide a comfortable room temperature for the consumer. In this optimisation, the maximum and minimum temperatures were 25^{o}C and 21^{o}C. Temperature starting of 22^{o}C was chosen. Under DSR program the cycling temperature room was longer than without DSR program. This is to give more option and more flexibility for the optimisation. In addition, since the price spike may occur in the middle of the day, the consumer is required to optimise to achieve minimum expected energy costs.

Under the DSR program, the control system applied the pre-cooling method to avoid high costs when a spike happens. Similar to the previously described method, the air conditioning was turned on once the temperature rose to the maximum permitted temperature. Then, it was turned off when the temperature dropped to the minimum permitted temperature. The control system kept the room temperature between the maximum and minimum permitted temperatures.

If S_s is the electricity price when a spike occurs, C_s is the market cost for spike cases, and K is the penalty, then the total market cost for the spike case (MC_s) is determined by the following equation:

$$MC_s(t) = \int_{t=1}^{t=n} [\, C_s(t) \;\; dt \,] + K \qquad (5.3)$$

$$MC_s(t) = \int_{t=1}^{t=n} [(\, S_s(t) \,.\, P(t).\, D(t).\, U(t)) \;\; dt \,] \; + K \qquad (5.4)$$

5.4.1 Half Hour Spike Case

Equations (4.3) to (4.6) and (5.3) and (5.4) were used to compute the numerical results of optimisation of the air conditioning when a half hour spike may occur in the middle of the day, as shown in Figure 5-2 and Tables 5-4 to 5-5.

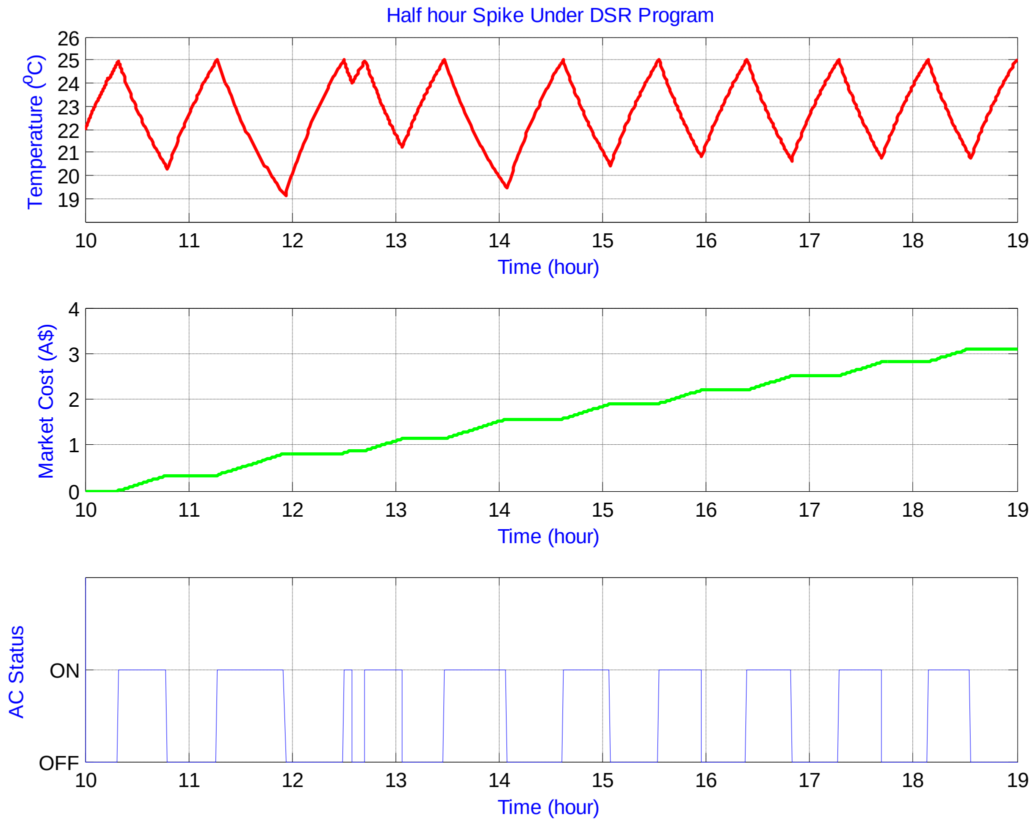

Figure 5-2: Numerical results of half hour spike case

Figure 5-2 illustrates the numerical results of the air conditioning optimisation when a price spike may occur in the middle of the day for half an hour. The cost can be minimised by maintaining the temperature of the room between the lower to upper temperatures. The typical operation is similar to the previously described method (i.e., the method without the DSR program) as discussed above. However, the air conditioning controller should be applying the pre-cooling method before a spike happens in order to avoid the price spike that may occur in the middle of the day. This is because there is a substantial risk of the price spike. Therefore, the room temperature will be cooler in the period leading up to the higher price time.

As Figure 5-2 indicates, a pre-cooling method was applied at switch number 4 before a spike happened. The temperature during the pre-cooling period dropped to a lower level (19^{o}C), which was cooler than the temperature during the spike period. The air conditioning status starting from the spike period was off until the duration of the spike had nearly expired. Due to the expensive cost, the control system turned on the air conditioning only for a short time during the spike period. As a result, the room temperature only dropped to 24^{o}C.

The calculation of the cost was based on the air conditioning status, with the electricity cost calculated when the air conditioning was switched on. The electricity costs were not calculated when the air conditioning is off. The market cost of the price spike was paid by the consumer when the air conditioning is on during the spike period. In addition, the consumer paid a normal price spike when the air conditioning was on during the no-spike periods. The total market cost (MC_{30}) and the penalty (K_{30}) that occur as a result of the optimisation are given in Table 5-5.

Table 5-4: Optimisation of half hour spike case

Switch Number	Time to Switch On/Off	AC Status	Switch Number	Time to Switch On/Off	AC Status
1	10:19	ON	11	14:37	ON
2	10:48	OFF	12	15:04	OFF
3	11:17	ON	13	15:32	ON
4	11:56	OFF	14	15:57	OFF
5	12:30	ON	15	16:23	ON
6	12:35	OFF	16	16:49	OFF
7	12:42	ON	17	17:16	ON
8	13:04	OFF	18	17:41	OFF
9	13:28	ON	19	18:08	ON
10	14:04	OFF	20	18:33	OFF

Table 5-5: Total market cost and penalty of half hour spike case

MC_{30} (A$)	**C_{30} (A$)**	**K_{30} (A$)**
3.11	3.11	0.0012

5.4.2 One Hour Spike Case

Equations (4.3) to (4.6) and (5.3) to (5.4) were used to compute the numerical results of optimisation of the air conditioning when a half hour spike may occur in the middle of the day, as shown in Figure 5-3 and Tables 5-6 and 5-7.

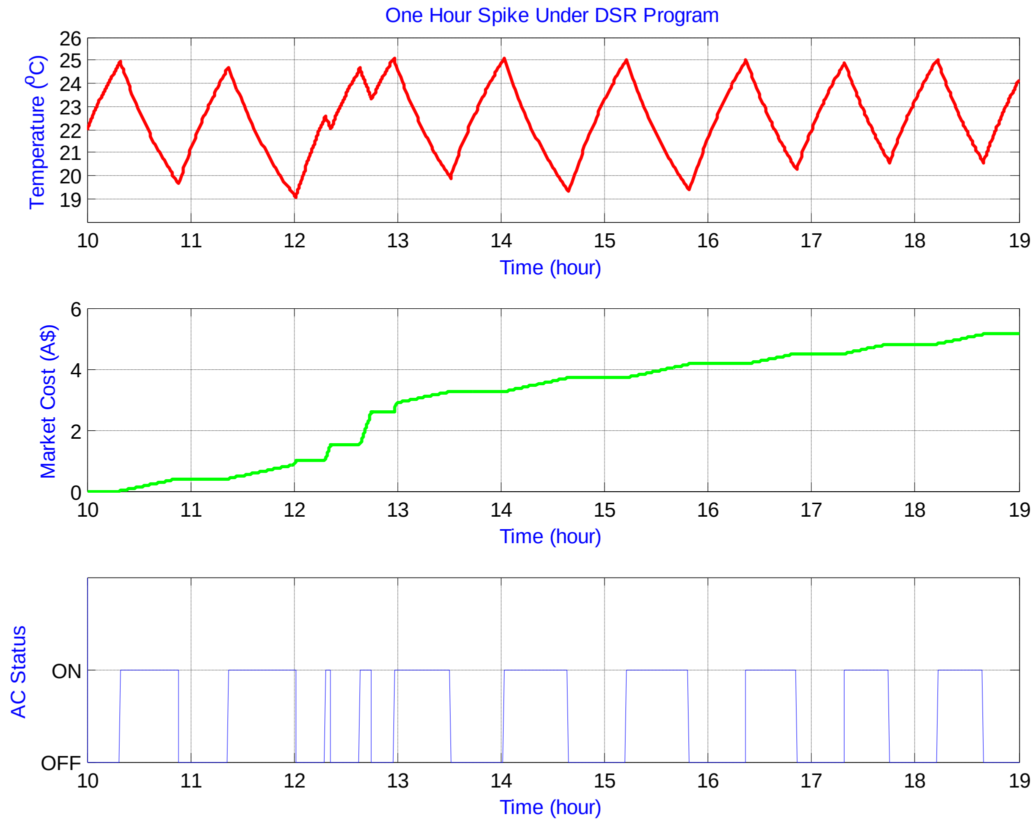

Figure 5-3: Numerical results of one hour spike case

The results reported in Figure 5-3 indicate that a price spike of one hour may occur in the middle of the day. The typical operation of the air conditioning was similar to the half hour spike case discussed above. A pre-cooling method was applied at switch number 4. The temperature during the pre-cooling dropped to 19°C, cooler than the temperature during the spike period. The air conditioning status when the spike started was off. Due to the high cost, the control system turned the air conditioning on only for a short time while the spike happened. The inside room temperatures were under 25°C and above 19°C.

Similar to the process explained above, the cost can be calculated according to the air conditioning status. There was a cost when the air conditioning is on and no cost when the air conditioning was off. Due to the duration of the spike, the consumer paid a higher cost than for the half hour spike. The market cost (MC_{60}) and penalty (K_{60}) that occurred as a result of the optimisation are given in Table 5-7.

Table 5-6: Optimisation of one hour spike case

Switch Number	Time to Switch On/Off	AC Status	Switch Number	Time to Switch On/Off	AC Status
1	10:19	ON	11	14:01	ON
2	10:53	OFF	12	14:39	OFF
3	11:22	ON	13	15:12	ON
4	12:01	OFF	14	15:49	OFF
5	12:18	ON	15	16:22	ON
6	12:21	OFF	16	16:51	OFF
7	12:38	ON	17	17:19	ON
8	12:45	OFF	18	17:45	OFF
9	12:58	ON	19	18:13	ON
10	13:30	OFF	20	18:39	OFF

Table 5-7: Total market cost and penalty of one hour spike case

MC_{60} (A$)	**C_{60} (A$)**	**K_{60} (A$)**
5.16	5.13	0.03

5.4.3 One and Half Hour Spike Case

Equations (4.3) to (4.6) and (5.3) to (5.4) were used to compute the numerical results of optimisation of the air conditioning when a half hour spike may occur in the middle of the day, as shown in Figure 5-4 and Tables 5-8 and 5-9.

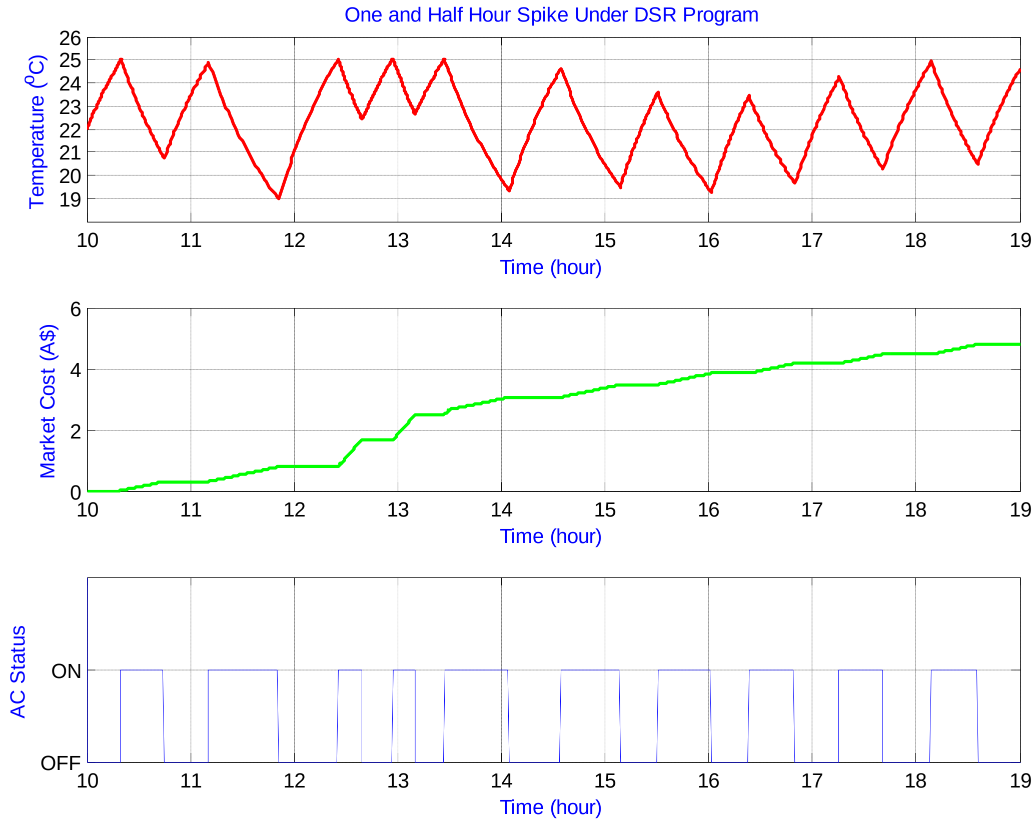

Figure 5-4: Numerical results of one and a half hour spike case

Figure 5.4 indicates that a price spike of one and a half hour duration may occur in the middle of the day. Similar to the one hour spike case, the pre-cooling method was applied to the entry period of the spike time at switch number 4. The temperature during the pre-cooling period dropped to the minimum permitted temperature, 19^{o}C. The temperature during the spike dropped to no less than 22^{o}C. As a result, the inside room temperature during the spike period was a little hot. In addition, the inside room temperature was above 22^{o}C until the spike expired. Once the time of the spike was expired, the air conditioning was turned on to drop the temperature to a lower threshold, that is, above the minimum permitted temperature of 19^{o}C.

Similar to the process described above, the cost was calculated based on the air conditioning status related to the duration of the spike and the length of time the air conditioning was on. The cost of a price spike was paid by the consumer when the air conditioning status was on during the spike period. Due to the duration of the spike, the air conditioning must be turned on three times until the time of the spike expired, as shown in Figure 5.4. The total market cost of the one and half hour spike was smaller than the one hour spike. This was because the nominal price of the one hour spike was higher than for the one and a half hour spike, even though the duration of the one and half hour spike was longer. The total market cost (MC_{90}) and penalty (K_{90}) that occurred as a result of the optimisation are given in Table 5-9.

Table 5-8: Optimisation of one and a half hour spike case

Switch Number	Time to Switch On/Off	AC Status	Switch Number	Time to Switch On/Off	AC Status
1	10:20	ON	11	14:34	ON
2	10:45	OFF	12	15:08	OFF
3	11:10	ON	13	15:30	ON
4	11:51	OFF	14	16:01	OFF
5	12:25	ON	15	16:23	ON
6	12:39	OFF	16	16:50	OFF
7	12:57	ON	17	17:15	ON
8	13:10	OFF	18	17:40	OFF
9	13:27	ON	19	18:08	ON
10	14:05	OFF	20	18:35	OFF

Table 5-9: Total market cost and penalty of one and a half hour spike case

MC_{90} (A$)	**C_{90} (A$)**	**K_{90} (A$)**
4.79	4.76	0.00276

5.5 COST AS A FUNCTION OF THE PROBABILITY OF A PRICE SPIKE

An electricity price spike may occur at any time during a day. To consider the case where there is a finite probability that a price spike may occur at the middle of the day, then we needed a new form of optimisation. Here we did not know what the price would be, so we forced the switching to be the same up until the spike time.

The switching would be different from that time onwards, depending on whether the spike really occurred. In this case, there were four switches which characterised the time up to the price event and a remaining 16 switches under the two switching scenarios. This gave a total of 36 switch edges to optimise. In this research, the probability of a half hour spike was 2.2%, a one hour spike was 0.8% and a one and a half hour spike was 0.5%.

To consider when there is a finite probability (P_D) that a price spike will occur in the system, we computed MC_n as the total market cost without a spike occurring and MC_s as the total cost assuming a spike occurs. The total market cost considering the probability (TMC) is thus given as the following equation:

$$TMC = MC_S(t) * P_D + MC_n(t) * (1 - P_D) \qquad (5.5)$$

Subject to constraints:

$$MC_s(t) = \int_{t=1}^{t=n} [(S_s(t) . P(t). D(t). U(t)) \ dt] + K \qquad (5.6)$$

$$MC_n(t) = \int_{t=1}^{t=n} [(S_n(t) . P(t). D(t). U(t)) \ dt] + K \qquad (5.7)$$

5.5.1. Half Hour Spike Case

Equations (4.3) to (4.6) and (5.5) to (5.7) were used to compute the numerical results of optimisation of the air conditioning considering the probability that a half hour spike may occur in the middle of the day, as shown in Figures 5-5 to 5-6 and Tables 5-10 and 5-11.

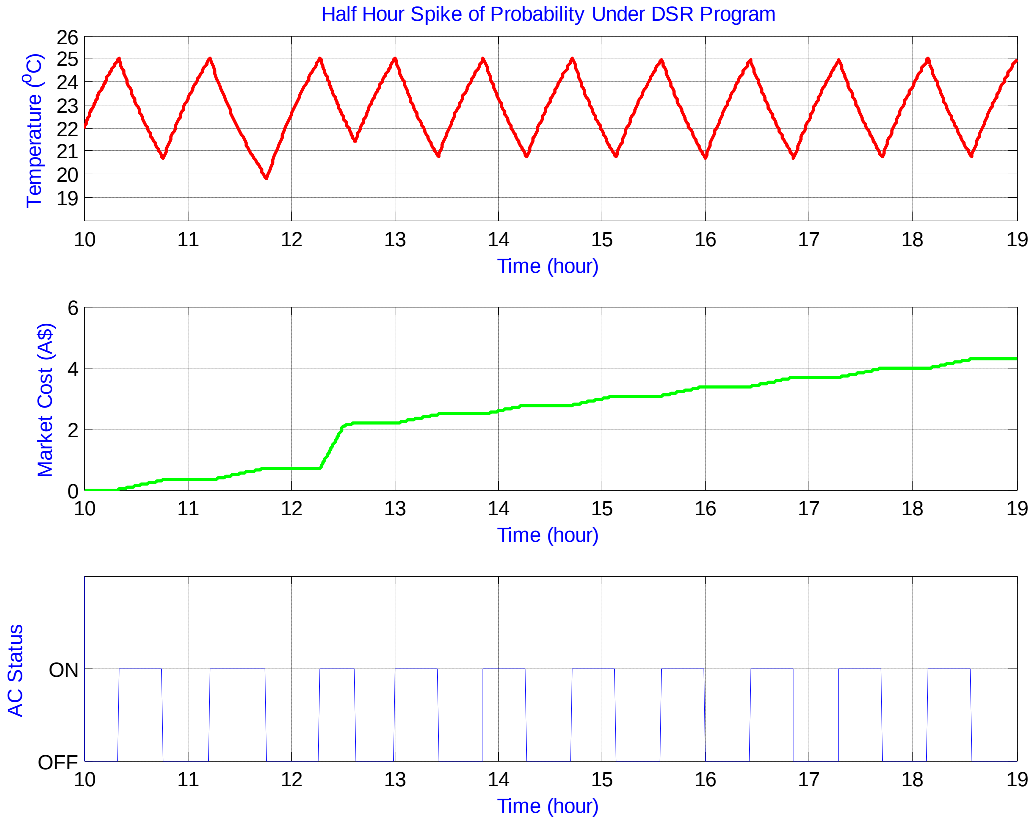

Figure 5-5: Numerical results of half hour spike probability case

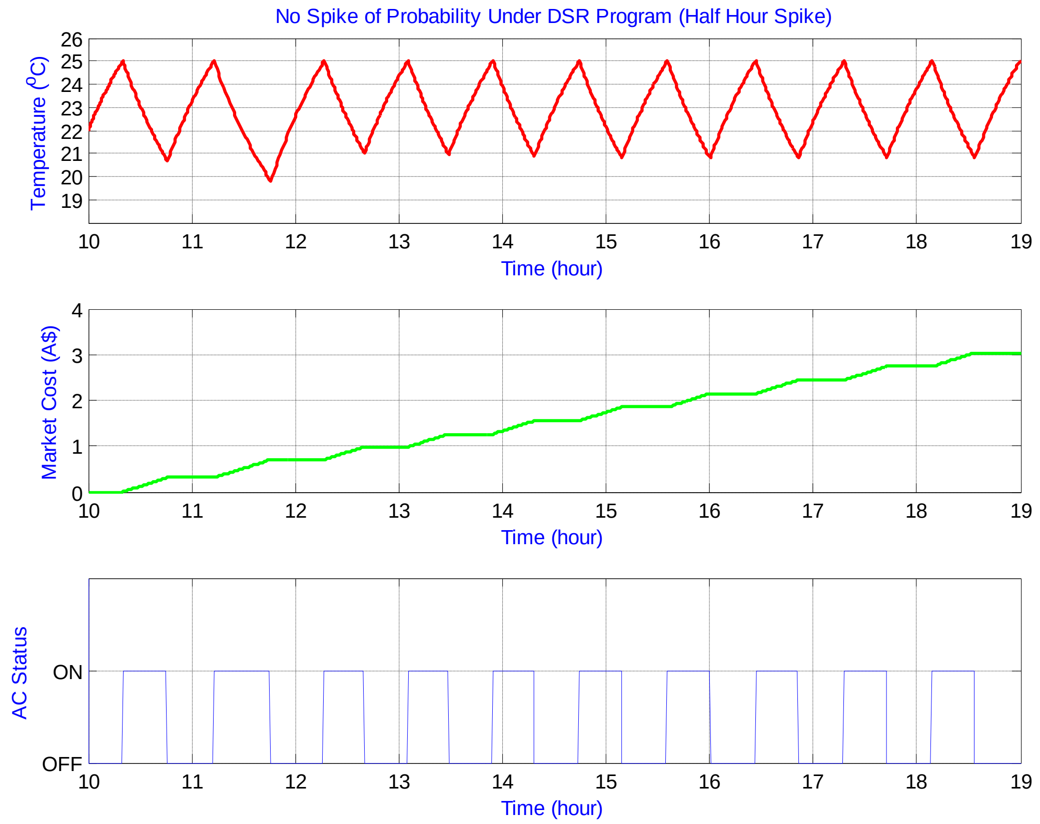

Figure 5-6: Numerical results of no-spike probability case (half hour spike case)

Figures 5-5 and 5-6 indicate the numerical results of air conditioning optimisation if a spike may occurs (with 2.2% probability) and no spike may occurs (with 97.8% probability) in the middle of the day. The inside room temperatures were under the maximum permitted temperature and above the minimum permitted temperature. Figures 5-5 and 5-6 illustrate that the time and inside room temperature for switch numbers 1 to 4 were equal. This is because, during this time, the probability of a spike was not considered. In contrast, due to the probability of the spike in the middle of the day, the characteristics of switch numbers 5 to 20 were not identical.

Figure 5-5 demonstrates the application of a pre-cooling method before a spike happens in the middle of the day. The room temperature dropped to less than 20^{o}C. This temperature is called a pre-cooling temperature. The air conditioning status when the spike started to happen was off until the duration of the spike was nearly expired. As a result, the room temperature when the spike happened dropped to 21^{o}C. In contrast, as the spike probability was not considered for the no-spike case, the room temperature dropped to 21^{o}C, as shown in Figure 5-6.

It is clear from Figures 5-5 that a pre-cooling method was necessary to minimise the energy cost if considering the spike probability. The control system applied a pre-cooling method to avoid expensive cost when the spike happens. This was because there is a substantial risk of the price spike. The total cost could then be numerically optimised by varying the 36 switch edges. There were 20 switches of spike cases and 20 switches of no-spike, with a remaining 16 switches for both of them under different scenarios. Similar to the process described above, the cost could be calculated according to the air conditioning status. The cost of a price spike case was more expensive than the cost of a no-spike case. The total market cost and penalty are given in Table 5-11.

Table 5-10: Optimisation of half hour spike probability

Switch Number	Time to Switch On/Off		AC Status	Switch Number	Time to Switch On/Off		AC Status
	No Spike	Spike			No Spike	Spike	
1	10:20	10:20	ON	11	**14:44**	**14:42**	ON
2	10:46	10:46	OFF	12	**15:09**	**15:08**	OFF
3	11:13	11:13	ON	13	**15:35**	**15:34**	ON
4	11:46	11:46	OFF	14	**16:00**	**15:59**	OFF
5	**12:17**	**12:16**	ON	15	**16:26**	**16:25**	ON
6	**12:40**	**12:37**	OFF	16	**16:52**	**16:51**	OFF
7	**13:05**	**13:00**	ON	17	**17:18**	**17:17**	ON
8	**13:29**	**13:25**	OFF	18	**17:43**	**17:42**	OFF
9	**13:54**	**13:51**	ON	19	**18:09**	**18:08**	ON
10	**14:18**	**14:16**	OFF	20	**18:33**	**18:34**	OFF

Table 5-11: Total market cost and penalty of half hour spike probability

TMC (A$)	Spike			No Spike		
	MC_{30} (A$)	**C_{30} (A$)**	**K_{30} (A$)**	**MCn (A$)**	**Cn (A$)**	**K (A$)**
3.06	4.27	4.27	0.0014	3.03	3.03	0.0012

5.5.2. One Hour Spike Case

Similar to the process explained above, a price spike may occur for one hour in the middle of the day. Figures 5-7 and 5-8 illustrate the numerical results of air conditioning optimisation if a spike may occur (with 0.8% probability) and no spike may occur (with 99.2% probability) and in the middle of the day. Equations (4.3) to (4.6) and (5.5) to (5.7) were used to compute the numerical results of optimisation, as given in Figures 5-7 and 5-8 and Tables 5-12 and 5-13.

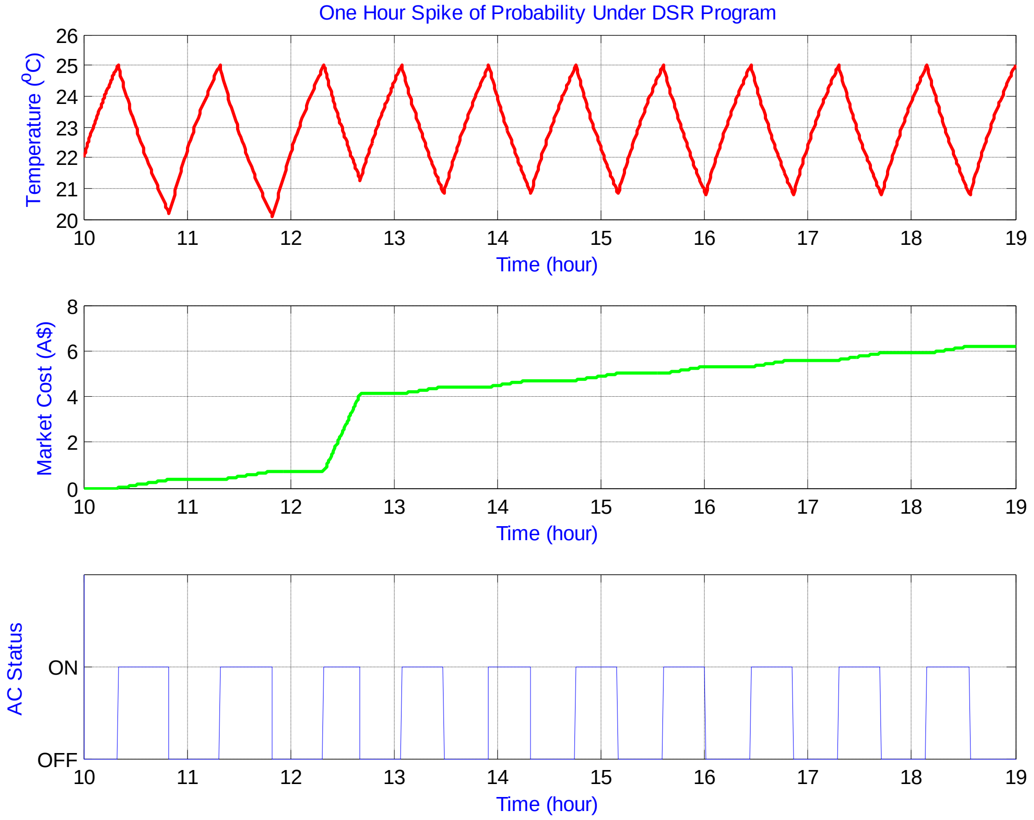

Figure 5-7: Numerical results of one hour spike considering spike probability

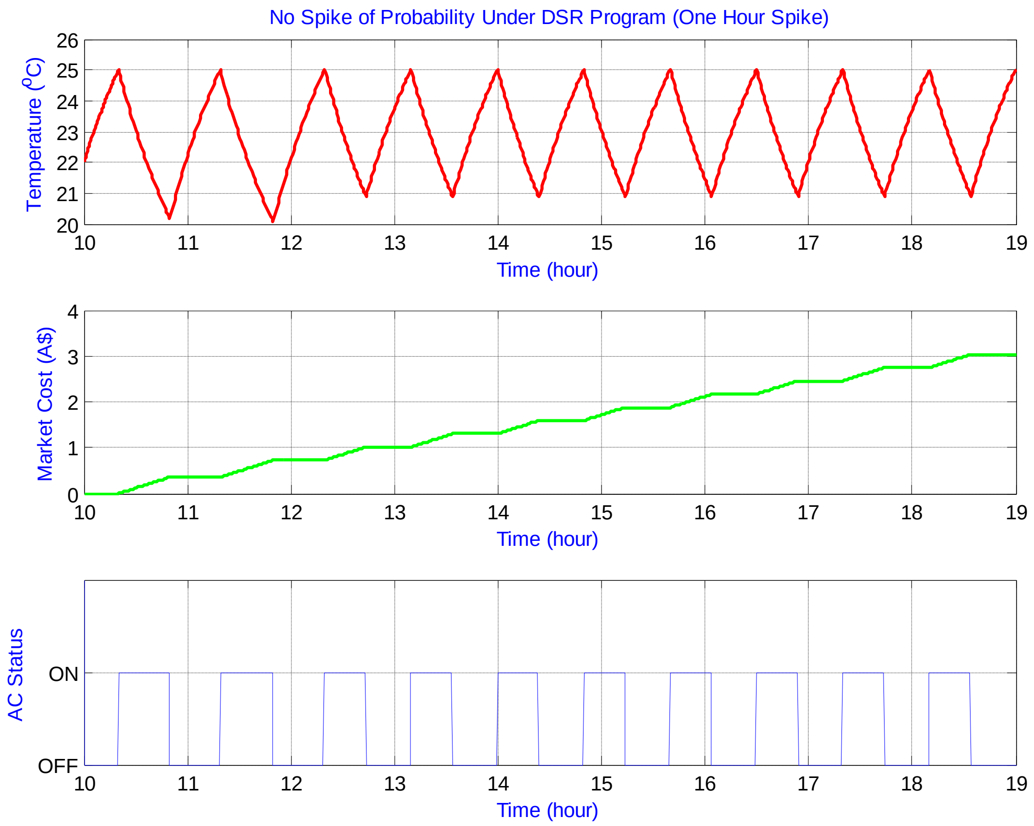

Figure 5-8: Numerical results of no-spike probability (one hour spike case)

Figures 5-7 and 5-8 illustrate the results of numerical optimisation if a spike may occur at the middle of the day for one hour. The result of optimisation with consideration of the spike probability is illustrated in Figure 5.7. In contrast, Figure 5.8 indicates the result of optimisation without considering the spike probability. Due to the probability of a spike in the middle of the day, the characteristics of switch numbers 1 to 4 in Figures 5-7 and 5-8 were equal. Only the characteristics of switch numbers 5 to 20 were not identical.

It is clear from Figure 5-7 that the pre-cooling method was applied to anticipate a price spike in the middle of the day. Similar to the previously described optimisation, the pre-cooling method was applied to the entry period of the spike. The air conditioning status when the spike happened was off. Due to the potential risk of a price spike, the control system still applied the pre-cooling method. The room temperature when the spike happened dropped to 21.2^{o}C. On the other hand, due to not considering the spike probability, the air conditioning dropped the temperature to less than 21^{o}C, as given in Figure 5-8.

There were 36 switches that could be optimised to calculate the total cost. The costs of the spike cases and no-spike each required 20 switches for optimisation. Similar to the process described above, the cost was calculated according to the air conditioning status. Due to the duration of the spike, the total cost of a one hour spike was more expensive than for a half hour spike. The total market cost and penalty are given in Table 5-13.

Table 5-12: Optimisation of one hour spike probability

Switch Number	Time to Switch On/Off		AC Status	Switch Number	Time to Switch On/Off		AC Status
	No Spike	Spike			No Spike	Spike	
1	10:20	10:20	ON	11	**14:49**	**14:45**	ON
2	10:49	10:49	OFF	12	**15:13**	**15:09**	OFF
3	11:19	11:19	ON	13	**15:39**	**15:36**	ON
4	11:49	11:49	OFF	14	**16:03**	**16:00**	OFF
5	**12:20**	**12:19**	ON	15	**16:29**	**16:26**	ON
6	**12:44**	**12:40**	OFF	16	**16:53**	**16:51**	OFF
7	**13:09**	**13:04**	ON	17	**17:19**	**17:17**	ON
8	**13:33**	**13:28**	OFF	18	**17:44**	**17:42**	OFF
9	**13:59**	**13:55**	ON	19	**18:09**	**18:08**	ON
10	**14:23**	**14:19**	OFF	20	**18:34**	**18:33**	OFF

Table 5-13: Total market cost and penalty of one hour spike probability

TMC (A$)	Spike			No Spike		
	MC_{60} (A$)	**C_{60} (A$)**	**K_{60} (A$)**	**MCn (A$)**	**Cn (A$)**	**K (A$)**
3.06	6.19	6.19	0.0009	3.03	3.03	0.0005

5.5.3. One and a Half Hour Spike Case

Figures 5-9 to 5-10 indicate the numerical results of air conditioning optimisation if a spike may occurs (with 0.5% probability) and no spike may occurs (with 99.5% probability) in the middle of the day and. The results of this optimisation, given in Figures 5-9 and 5-10 and Tables 5-14 to 5-15, were calculated by Equations (4.3) to (4.6) and (5.5) to (5.7).

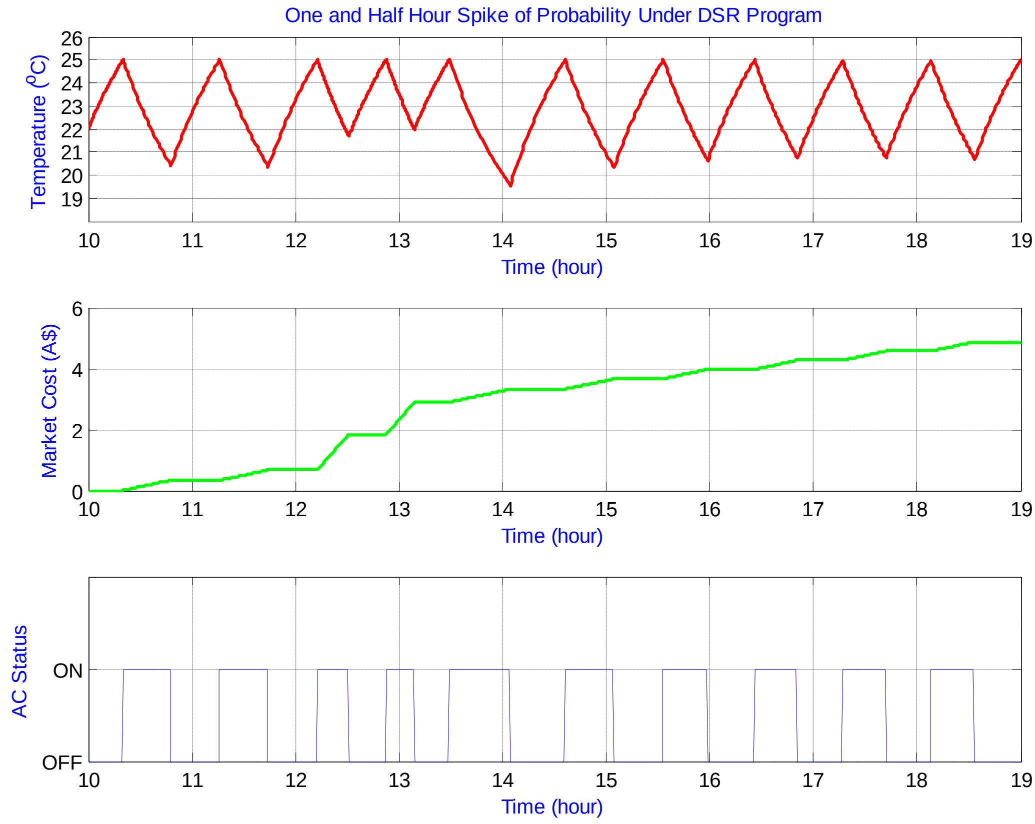

Figure 5-9: Numerical results of one and a half hour spike probability

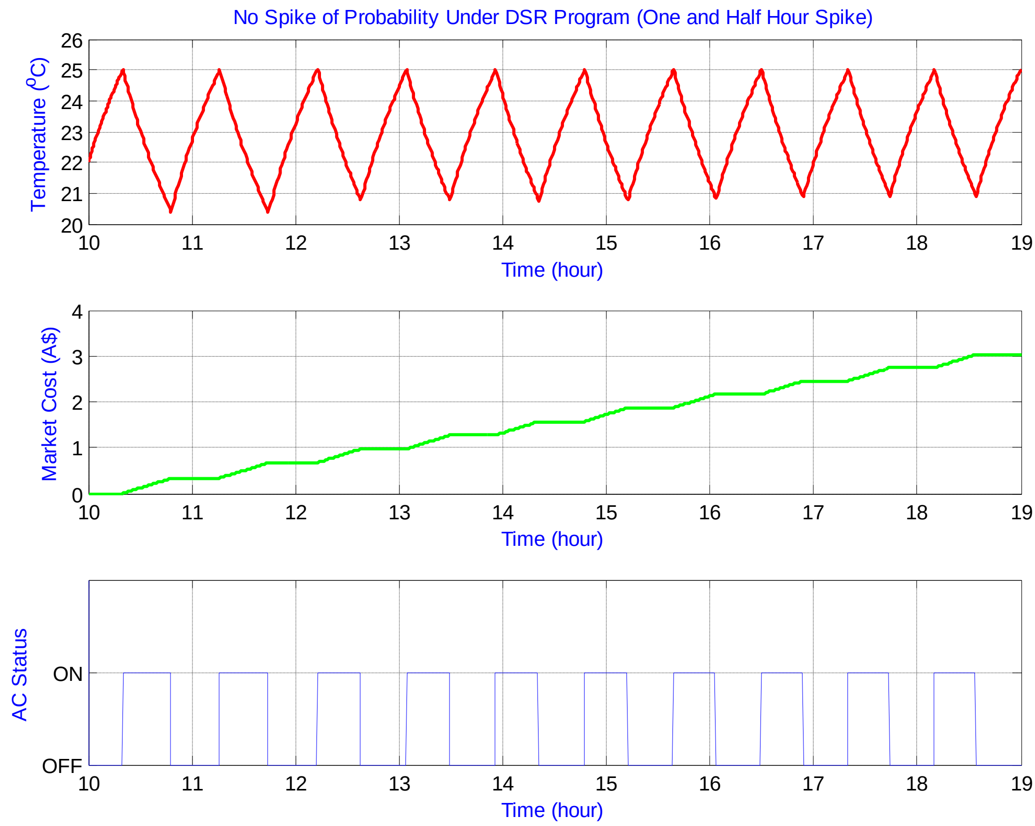

Figure 5-10: Numerical results of no-spike probability (one and half hour spike case)

As illustrated in Figure 5-9, a pre-cooling method was applied to anticipate expensive cost when a spike happened in the middle of the day. This was because of the long duration of the spike and the substantial risk of the price spike. Consequently, the room temperature when the spike happened was hotter than previously. In order to keep the room temperature comfortable, the control system dropped the temperature to a lower level as soon as the time of the spike expired. In contrast, as indicated in Figure 5-9, the room temperature was optimised between the maximum and minimum permitted temperatures. The optimisation did not consider the spike probability. As a result, the control system did not apply the pre-cooling method.

Similar to the previous optimisation, the total cost could then be numerically optimised by varying the 36 switch edges. There were 20 switches in the spike cases and no-spike, with a remaining 16 switches for both of them under different scenarios. Only switch numbers 1 to 4 were equal for both simulations. Switch numbers 5 to 20 of the spike case were not identical to switch numbers 5 to 20 of the no-spike case. As a result, the result of both simulations was not similar due to the spike probability in the middle of day. The total market cost and penalty are presented in Table 5-15.

Table 5-14: Optimisation of one and a half hour spike probability

Switch Number	Time to Switch On/Off		AC Status	Switch Number	Time to Switch On/Off		AC Status
	No Spike	Spike			No Spike	Spike	
1	10:20	10:20	ON	11	**14:47**	**14:36**	ON
2	10:47	10:47	OFF	12	**15:12**	**15:04**	OFF
3	11:16	11:16	ON	13	**15:39**	**15:32**	ON
4	11:44	11:44	OFF	14	**16:03**	**15:59**	OFF
5	**12:13**	**12:12**	ON	15	**16:29**	**16:25**	ON
6	**12:37**	**12:30**	OFF	16	**16:54**	**16:50**	OFF
7	**13:04**	**12:53**	ON	17	**17:20**	**17:17**	ON
8	**13:29**	**13:08**	OFF	18	**17:44**	**17:42**	OFF
9	**13:56**	**13:30**	ON	19	**18:10**	**18:08**	ON
10	**14:21**	**14:04**	OFF	20	**18:34**	**18:33**	OFF

Table 5-15: Total market cost and penalty of one and a half hour spike probability

TMC (A$)	Spike			No Spike		
	MC_{90} (A$)	**C_{90} (A$)**	**K_{90} (A$)**	**MCn (A$)**	**Cn (A$)**	**K (A$)**
3.04	4.86	4.86	0.0008	3.03	3.03	0.0012

5.6 BENEFITS OF DSR PROGRAMS

Based on the results of the optimisation reported above, the consumer and aggregator could gain collective benefits when the consumer controls the air conditioning under the DSR program. The collective benefit (CB) is expressed by the following equation:

$$CB_{30,60,90} = MC_{1,2,3} - MC_{30,60,90} \quad (5.8)$$

If considering to the probability spike, the CB is expressed by the following equation:

$$CB_{30,60,90} = MC_{1,2,3} - TMC_{30,60,90} \tag{5.9}$$

The percentage of collective benefit is illustrated by the following equations:

$$\%\,(CB_{30,60,90}) = \frac{CB_{30,60,90}\ (A\$)}{MC_{1,2,3}\ \ (A\$)} \tag{5.10}$$

Equation (5.8) and (5.10) were used to compute the collective benefit. Table 5-16 summarises the collective benefit for the consumer and aggregator when the consumer applied the DSR program if a spike may only occur in the middle of the day.

Table 5-16: Collective benefit if spike may only occur in the middle of the day

Spike Duration	Total Market Cost			
	Without DSR $MC_{1,2,3}$ (A$)	**Under DSR $MC_{30,60,90}$ (A$)**	**Collective Benefit ($CB_{30,60,90}$)**	
			(A$)	**(%)**
Half hour	5.99	3.10	**2.89**	**48.25**
One hour	8.79	5.16	**3.63**	**41.29**
One and half hour	8.57	4.79	**3.78**	**44.10**

It is clear from the results presented in Table 5-16 that the collective benefits reached by the consumer and aggregator when the DSR program was applied were A$2.89 (48.25 %), A$3.63 (41.29 %) and A$3.78 (44.10 %) for a half hour spike, one hour spike, and one and a half hour spike case, respectively. This indicates that controlling the air conditioning temperature under the DSR program can minimise the energy cost. The pre-cooling method was required to anticipate a price spike in the electricity market if a price spike may only occur in the middle of the day.

Equation (5.9) and (5.10) were used to compute the collective benefit. Table 5-17 presents the collective benefits for the consumer and aggregator if a spike may occur in the middle of the day considering the probability of a price spike.

Table 5-17: Collective benefit if spike may only occur in the middle of the day considering the spike probability

Spike Duration	Total Market Cost			
	Without DSR $MC_{1,2,3}$ (A\$)	**Under DSR TMC $_{30,60,90}$ (A\$)**	**Collective Benefit ($CB_{30,60,90}$)**	
			(A\$)	**(%)**
Half hour	5.99	3.06	**2.93**	**48.91**
One hour	8.79	3.06	**5.73**	**65.18**
One and half hour	8.57	3.04	**5.53**	**64.52**

As presented in Table 5-17, the consumer and aggregator can earn collective benefits if the DSR program is applied to meet a price spike considering the spike probability; for example, 2.93 A\$ (48.91 %) for a half hour spike, 5.73 A\$ (65.18) for a one hour spike and 5.53 A\$ (64.52 %) for a one and a half hour spike. This result indicates the pre-cooling method was effective to minimise the energy cost when a spike happens. Even though the spike probability was smaller, the pre-cooling method was required to anticipate high costs when a spike happens. The pre-cooling method was only applied when there was a substantial risk of a price spike.

5.7 CONCLUSION

This chapter has demonstrated that the proposed DSR model allows consumers to manage and control air conditioning for every period based on the electricity market price. The model is applicable for both residential and commercial consumers to minimise the cost of fluctuating energy prices. The proposed model can assist the consumer to optimise the energy cost of air conditioning to meet a price spike and where spike probability cases occur in the middle of the day. Numerical modelling is a possible solution to minimise the energy cost by optimising the temperature room considering the varying electricity market price and outside temperature. This result indicates that, the consumer should apply the pre-cooling method to minimise energy costs by anticipating the electricity price spike when we know the spike may occur in the middle of the day. In addition, a pre-cooling method should be applied to avoid high electricity prices at critical times. However, pre-cooling should only be undertaken when there is a substantial risk of a price spike.

The pattern of the air conditioning controlled without the DSR program was discussed in Section 5.3. Due to the price spike in the middle of the day, the consumer must pay high costs. The total market cost was based on the duration of the spike and the nominal price of every spike duration. The room temperature stayed between the maximum and minimum permitted temperatures. As a result, the pre-cooling method was not applied in the system.

Section 5.4 discussed the proposed DSR model to minimise the air conditioning energy cost to meet a price spike in the electricity market that may only occur in the middle of day. The pre-cooling method was applied to minimise the energy cost if there was a substantial risk of the price spike. The pre-cooling method was applied to meet a price spike of a half hour, one hour, and one and a half hour duration. As a result, the cost could be minimised.

Section 5.5 discussed the proposed DSR model to minimise the energy cost for the air conditioning to meet a price spike in the electricity market which may occur in the middle of the day considering the probability of a spike. To avoid expensive cost when a spike happens, the control system applied the pre-cooling method. This method was effective to minimise the energy cost because the air conditioning status was off until the spike nearly expired and the air conditioning was turned on for a short time when the spike happened. The spike probability had a significant impact on defining the total cost, and justifying the pre-cooling method was required. As this result indicates, the pre-cooling method was applied for spikes of all duration.

In Section 5.6, the benefits of the DSR program were discussed. The collective benefits for the consumer and aggregator were obtained if the consumer applied the DSR program to control the air conditioning temperatures. The collective benefit of spikes of all duration was obtained if the spike may only occur in the middle of the day as well as considering the spike probability.

Based on the result of optimisation indicated that based on the parameters of the room and air-conditioning, the electricity market price data from the AEMO during weekdays on hot days from 2011 to 2012, this model is only appropriate when we know a price spike of electricity market may occur in the middle of the day as well as considering to the probability market price. However, due to unpredictable electricity market price during a day, this model still not solve for the real problem. A price spike of electricity market may occur at any time a day. Although, it is recommended to the consumer to approach this model if a price spike of electricity market price may only occur in the middle of the day.

Chapter 6: Case of Defining Expected Cost for the Air Conditioning to Avoid a Price Spike of Electricity Market

6.1 INTRODUCTION

This chapter describes the DSR model used by the consumer/aggregator to minimise the total expected market cost by optimising the air conditioning to account for occurrences of a price spike. Section 6.2 describes the methodology of the case study. Section 6.3 describes the total expected market cost when the temperature does not reach the maximum temperature during the spike period. Section 6.4 describes the total expected market cost which causes the maximum temperature to be reached during the spike period. Section 6.5 describes the case study. Finally, Section 6.6 concludes this chapter.

6.2 DESCRIPTION OF METHODOLOGY IN CASE STUDY 2 – HOURLY SPIKE TIME MARKET ONLY CASE

In this study, we developed a model for estimating the total expected market cost for operating the air conditioning when being exposed to or responding to the market price through an aggregator. The estimation method examined the minimum total expected market cost as a function of the starting temperature when a price spike may occur at hourly. We applied this model to estimate the minimum total expected market cost using information on the outside temperature and electricity price probability. This model is only appropriate to define the total expected cost if hourly spike time for market only case.

In this chapter, we describe two main points of the price spike model based on the typical spike, namely, a spike when the temperature does not reach the maximum temperature during the spike period and a spike which causes the maximum temperature to be reached. The maximum and minimum permitted temperatures were 25^{o}C and 19^{o}C, respectively. When a normal operating temperature is selected in practice, the temperature would be cycled between limits near the reference. For example, a reference temperature of 20^{o}C requires cycling between 19^{o}C to 21^{o}C.

In this simulation, an inside room temperature of 19^{o}C to 25^{o}C is chosen. However, the expected temperature is used to analyse the total expected cost. Four kinds of expected temperatures were used to analyse this data, namely when the starting temperature (Ts) is between 19^{o}C to 21^{o}C. Controlling the room temperature between 19^{o}C to 21^{o}C, the air-conditioning is turned on when the temperature rises to 21^{o}C, then turned off once the temperature drops to a minimum threshold of 19^{o}C. As a result, it is necessary to cycle those temperatures to obtain 20^{o}C as the expected temperature. This method is used to define the expected temperature when starting temperature between 22^{o}C to 24^{o}C, 19^{o}C to 24^{o}C and 24^{o}C to 26^{o}C.

Numerical modelling is a feasible solution to allow for unpredictable market price changes due to the interruption of a major generation or other supply-side constraints. This model shows how the air conditioning should decrease the temperature loads at high temperature periods when there is a substantial risk of a price spike, that is, by applying the pre-cooling method. The pre-cooling method is regarded as more effective because it can emerge as the optimal solution when the risk of a spike is high.

The objective function is to minimise the expected market cost for the air conditioning. The minimum expected market cost is based on the starting temperature when a price spike may occur. In order to formulate the participation of the consumer in the DSR program, the expected market cost model which represents the changed temperature and electricity price was developed in this study. The minimisation problem could be represented as the minimised expected market cost (EZ), or mathematically:

$$\mathrm{EZ(t)} = \int_{t=1}^{t=n} [(\mathrm{EC(t)}\ dt \qquad (6.1)$$

$$EZ(t) = \int_{t=1}^{t=n} [(S(t) \, . \, P(t). \, D(t). \, U(t)) \;\; dt \,] \qquad (6.2)$$

Table 6-1 summarises the parameters of the typical room and the air conditioning used in this optimisation. Similar to the simulations in the previous chapter, due to the high outside temperature, the air conditioning operation was from 10:00 to 19:00.

Table 6-1: Parameters of the example room used in this analysis

No.	Parameter	Value	Unit
1	Heat transfer coefficient from floor wall and ceiling (Q)	1	$W/m^2\,{}^oC$
2	Total area (A)	54	m^2
3	Heat capacity of the room (H)	48	$J/{}^oC$
4	Heat transfer from the air conditioning (B)	900	W
5	Maximum temperature	25	^oC
6	Minimum temperature	18	^oC
7	Rating power of air conditioning (P)	2.6	kW

6.3 CASE 1 – SPIKE WHEN THE TEMPERATURE DOES NOT REACH THE MAXIMUM DURING SPIKE PERIOD

This model sets up temperatures starting from 19^{o}C to 21^{o}C as a comfortable temperature limit of the room. The expected temperature is 20^{o}C. In this model, we initially only considered a spike duration of (D_s) 0.5 hours. To avoid high market costs when the spike occurs, this model set the air conditioning status as off; $U = 0$. The inside room temperature would increase up to the high temperature (T_h). At the end of the spike, the air conditioning status was 'ON' to drop the temperature to the low level (T_l) because of the possibility that a second spike may occur. As a result, the air conditioning did not require high power (P_h) to keep the temperature at this level. This is shown in Figure 6-1.

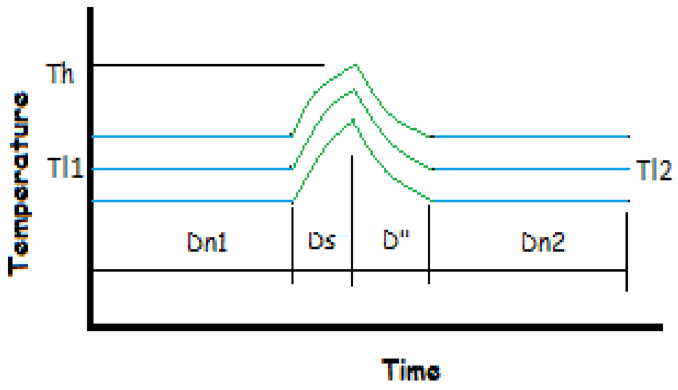

Figure 6-1: Spike based on high temperature

The expected market cost when no spike occurs before spike (EMC_{n1}) was determined by multiplying low power (P_l) by the electricity non-spike price (S_n) during the time before spike (D_{n1}), as shown in the following equation:

$$EMC_{n1}(t) = \int_{t=1}^{t=n} [(S_n\,(t) * P_l\,(t) * D_{n1}(t))\,dt\,] \qquad (6.3)$$

The expected market cost when no spike occurs after spike (EMC_{n2}) was determined by multiplying low power (P_l) by the electricity non-spike price (S_n) during the time after spike (D_{n2}), as shown in the following equation:

$$EMC_{n2}(t) = \int_{t=1}^{t=n} S_n\,(t) * P_l\,(t) * (D_{n2}(t) + D''(t)) \qquad (6.4)$$

Calculation of the expected market cost when a spike occurs (EMC_s) was not required because the high power (P_s) was equal to zero. To consider when there is a finite probability that a price spike will occur in the system (P_D), we computed $EMCost_n$ as the total expected market cost without a spike occurring and $EMCost_s$

as the total expected market cost assuming a spike occurs. The total expected market cost considering probability (ETMC) is thus given in the following equation:

$$ETMC(t) = EMCost_s(t) * P_D(t) + EMCost_n(t) * \left(1 - P_D(t)\right) \quad (6.5)$$

Subject to constraints as follows:

$$EMCost_s(t) = EMC_{n1}(t) + EMC_{n2}(t) \qquad (6.6)$$

$$EMCost_n(t) = \int_{t=1}^{t=n} [\left(S_n(t) * P_l(t) * \left(D_{n1}(t) + D_s(t) + D_{n2}(t)\right)\right) dt] \qquad (6.7)$$

If we want to maintain the expected low temperature (T_l), then the air conditioning requires a higher power of (P_s). Similar to maintaining the expected maximum temperature (T_{max}), the air conditioning requires a lower power of (P_n). The low power and high power required are calculated by the following equations:

$$P_s(t) = \frac{P_{max} * (T_0(t) - T_l(t))}{(T_0(t) - T_{min})} \qquad (6.8)$$

$$P_n(t) = \frac{P_{max} * (T_0(t) - T_{max}(t))}{(T_0(t) - T_{min})} \qquad (6.9)$$

6.4 CASE 2 – SPIKE WHICH CAUSES THE MAXIMUM TEMPERATURE TO BE REACHED

In this model, the starting temperature (Ts) could be set from 22^{o}C to 24^{o}C considering only the 0.5 hour spike problem. In addition, this model was appropriate for spike duration (D_s) $\geq$ 1 hour with starting temperatures from 19^{o}C to 24^{o}C. As mentioned above, the expected low temperature (T_l) for 22°C to 24°C was 23°C, for 19°C to 24°C it was 21.5°C, and the expected maximum temperature (ET_{max}) was 25°C.

Due to the duration of the spike, the room temperature rose up to ET_{max}. This event is called the off time (D'). Once the temperature was up to this level, the air conditioning was then on to maintain ET_{max} until the spike had expired; the duration of this event is called the expected-maximum time spike duration (D_t). At the end of the spike, the air conditioning status remained on to drop the temperature from ET_{max} to the low level (T_l) because of the possibility that a second spike may occur. This moment is called the on time (D''). Figure 6-2 illustrates this process.

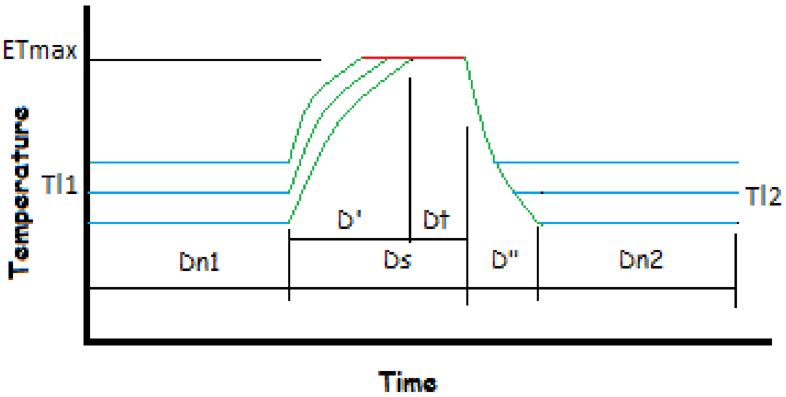

Figure 6-2: Spike based on expected maximum temperature

In determining the expected market cost, the expected market cost when no spike occurs before and after a spike is expressed in Equations (6.3) and (6.4). The expected market cost when a spike occurs (EMC_s) was determined by multiplying high power (P_s) by the electricity price spike (S_s) and by the expected-maximum time spike (D_t) as expressed in the following equation:

$$EMC_s(t) = \int_{t=1}^{t=n} [(S_s(t) * P_h(t) * D_t(t))\, dt] \qquad (6.10)$$

If the consumer operates the air conditioning during $\mathrm{D_t}$ period, they will face penalty (K). The penalty will be calculated as follows:

$$\text{If } \mathrm{ET(t) = ETmax} \text{ Then Penalty} = \mathrm{K} \qquad (6.11)$$

$$\text{Else Penalty} = 0 \qquad (6.12)$$

Therefore, $\mathrm{EMC_s(t)}$ will be calculated as follows:

$$\mathrm{EMC_s(t)} = \int_{t=1}^{t=n} [(\mathrm{S_s}(t) * \mathrm{P_h}(t) * \mathrm{D_t}(t))\, dt] + \mathrm{K} \qquad (6.13)$$

To consider when there is a finite probability that a price spike will occur in the system, we computed $\mathrm{EMCost_n}$ as the total expected market cost without a spike occurring and $\mathrm{EMCost_s}$ as the total expected market cost assuming a spike occurs. The total expected market cost (ETMC) is thus given as the following equation:

$$\mathrm{ETMC(t) = EMCost_s(t) * P_D(t) + EMCost_n(t) * \left(1 - P_D(t)\right)} \qquad (6.14)$$

Subject to constraints as follows:

$$\mathrm{EMCost_s(t) = EMC_{n1}(t) + EMC_s(t) + EMC_{n2}(t)} \qquad (6.15)$$

$$\mathrm{EMCost_n(t)} = \int_{t=1}^{t=n} \left[\left(\mathrm{S_n}(t) * \mathrm{P_l}(t) * \left(\mathrm{D_{n1}}(t) + \mathrm{D_s}(t) + \mathrm{D_{n2}}(t)\right)\right) dt\right] \qquad (6.16)$$

The determination of (D') and (D'') is by approximation of the linear transition from low to high temperatures and from high to low temperatures, respectively. The problem can be represented as:

$$D'(t) = \frac{k1 * (T_h(t) - T_{l1}(t))}{(T_0(t) - T_{av1}(t))} \qquad (6.17)$$

$$D''(t) = \frac{k1 * (T_h(t) - T_{l2}(t))}{(T_0(t) - T_{av2}(t))} \qquad (6.18)$$

where k1 as a constant of a typical room can be calculated by the following equation:

$$k1 = \frac{Q.A}{H} \qquad (6.19)$$

The expected-maximum time spike D_t can be defined by the following expression:

$$D_t(t) = Ds(t) - D'(t) \qquad (6.20)$$

Determinations of the average temperature before and after a spike, T_{av1} and T_{av2}, are defined by this expression:

$$T_{av1}(t) = \frac{\left(T_{l1}(t) + ET_{max}(t)\right)}{2} \qquad (6.21)$$

$$T_{av2}(t) = \frac{\left(T_{l2}(t) + ET_{max}(t)\right)}{2} \qquad (6.22)$$

Therefore, determination of the total expected market cost for several spike cases is defined by this expression:

$$\mathrm{ETMC}(t) = \sum_{i=1}^{n} \mathrm{EMCost}_{si}(t) * P_{Di}(t) + \mathrm{EMCost}_{n}(t) * \prod_{i=1}^{n}(1 - P_{Di}(t)) \quad (6.23)$$

6.5 CASE STUDIES

The proposed price spike model was used to analyse data regarding the Queensland electricity market price in 2011 and 2012 during hot days. In this case, any day on which the average daily temperature was more than 30^{o}C is called a hot day. Based on the spike time duration, there were several cases of a price spike during hot days in 2011-2012. In this chapter, we consider spikes in three categories (half hour, one hour, and one and a half hour spikes) for analysis. A price spike case of two hours or more than two hours was not considered because the probability of a price spike of more than 1.5 hours was very small. In addition, the temperature data on 29 February 2012 was selected to describe the outside temperature (To). As a result, this research shows the total expected market cost with the probability of an electricity price spike for the weekday period during hot days in 2011-2012. Some of the typical case study results are given in Tables 6.2 and 6.3.

6.5.1 Case 1 considering the half hour spike

Table 6-2 indicates the total expected market cost as a function of spike probability for 0.5 hours with possible starting temperatures (Ts) from 19^{o}C to 21^{o}C and 22^{o}C to 24^{o}C. Equations (6.3) to (6.8) above were used to compute the total expected market cost for Ts 19^{o}C to 21^{o}C, and Equations (6.9) to (6.22) were used to compute the total expected market cost for Ts 22^{o}C to 24^{o}C, as shown in Table 6-2.

Table 6-2: Total expected market cost for Case 1 with Ts=19°C -24°C

Start Time of Spike	Total Expected Market Cost (A$)					
	Ts=19°C	**Ts=20°C**	**Ts=21°C**	**Ts=22°C**	**Ts=23°C**	**Ts=24°C**
10:00	0.83	0.73	0.64	0.47	0.41	**0.36**
11:00	0.83	0.73	0.64	0.48	0.45	**0.43**
12:00	0.82	0.74	**0.66**	0.67	0.69	0.72
13:00	0.81	0.75	**0.68**	0.73	0.78	0.84
14:00	0.81	0.75	**0.70**	0.87	0.94	1.02
15:00	0.81	0.76	**0.71**	1.05	1.13	1.21
16:00	0.81	0.76	**0.70**	0.95	1.03	1.13
17:00	0.81	0.76	**0.70**	0.96	1.04	1.13
18:00	0.82	0.74	0.66	**0.53**	0.58	0.66
19:00	0.82	0.74	0.65	**0.49**	0.51	0.56

It is clear from the results presented in Table 6-2 that the total expected market cost for every different spike occurrence was based on the outside temperature, starting temperature and spike probability. The minimum total expected market costs were achieved at 10:00 to 11:00 when the selected normal operating temperature was 24°C, the outside temperature was lower and the spike probability was lower. This also occurred when the spike started at 18:00 and 19:00. This indicates there was no substantial risk for the price spike in this event. Therefore, pre-cooling was not required at these times. In contrast, from 12:00 to 17:00, the outside temperature and spike probability were higher so the minimum total expected market cost was achieved when the selected normal operating temperature was 21°C. This indicates that a small amount of pre-cooling was required to reach the minimum total expected market cost. The pre-cooling method should be applied to reach the minimum total expected market cost for these times.

Based on the result of the data analysis above, it is recommended that all consumers who seek to engage an aggregator to gain collective benefits should apply the pre-cooling method for operating the air conditioning when a price spike may occur for half hours if there is a substantial risk of a price spike. Here we see that, when the spike probability is high, pre-cooling is very effective to minimise energy costs.

6.5.2 Case 2 considering a half hour, one hour, and one and a half hour spike

The results presented in Table 6-3 indicate the total expected market costs as a function of a spike probability for 0.5 hour, 1 hour and 1.5 hour duration. The starting temperature was 19^{o}C to 24^{o}C. Therefore, the expected temperature was 21.5^{o}C. Equations (6.9) to (6.23) were used to compute the total expected market cost for this case for every different starting temperature as shown in Table 6-3.

Table 6-3: Total expected market cost for Case 2 with Ts=19^{o}C -24^{o}C

Spike Start Time	**Total Expected Market Cost (A$)**					
	Ts=19 ^{o}C	**Ts=20 ^{o}C**	**Ts=21 ^{o}C**	**Ts=22 ^{o}C**	**Ts=23 ^{o}C**	**Ts=24 ^{o}C**
10:00	2.23	2.04	1.88	1.74	1.64	**1.59**
11:00	2.25	2.11	2.01	1.94	**1.91**	1.95
12:00	2.55	2.52	**2.51**	2.55	2.63	2.77
13:00	**3.11**	3.16	3.24	3.36	3.52	3.72
14:00	**3.61**	3.72	3.85	4.03	4.23	4.49
15:00	**4.38**	4.54	4.71	4.92	5.15	5.42
16:00	**3.88**	4.03	4.21	4.42	4.67	4.97
17:00	**3.69**	3.80	3.93	4.09	4.27	4.50
18:00	2.33	**2.32**	2.34	2.41	2.54	2.74
19:00	2.22	2.14	2.10	**2.09**	2.13	2.24

There was a clear correlation between outside temperature, starting temperature and the probability of an electricity price spike related to the total expected market cost. The results presented in Table 6-3 show that the minimum total expected market cost was realised at 19^{o}C when the control system operated the air conditioning from 13:00 to 17:00 and 20^{o}C at 18:00. This was because the spike probability and outside temperature were higher than at other times. The data in this table also indicates that the pre-cooling method was required to reach the minimum total expected market cost. A small amount of pre-cooling should be applied to reach the minimum total expected market cost when the selected temperature was 21^{o}C at 12:00. Therefore, the consumer should apply this method to implement the minimum total expected market cost plan when the spike period is from 12:00 to 18:00. On the other hand, the minimum total expected market cost was achieved above the operating temperatures of 24^{o}C at 10:00, 23^{o}C at 11:00 and 22^{o}C at 19:00. This was because the outside temperature and spike probability were lower.

The data analysis indicates that the outside temperature, normal operating temperature starting and spike probability had a significant impact on defining the total expected market cost for every different period of spike. It is recommended that all consumers should apply the pre-cooling method for operating the air conditioning when the outside temperature and spike probability are high. Here we see that, when the spike probability and outside temperature are high, the pre-cooling is very effective to minimise energy costs. Pre-cooling is required if there is a substantial risk of a price spike.

6.6 CONCLUSION

The proposed innovative consumer DSR model is aimed at enabling consumers to determine the total expected market cost for operating the air conditioning. In this model, the temperature room was no considering to cycling temperature between maximum and minimum permitted temperature. When we know the outside temperature then control system could define the expected temperature. The model is applicable for both residential and commercial consumers to address fluctuating energy prices to minimise energy market costs for using the air conditioning and allows controlled tariff consumers to reach a collective benefit with their aggregator. The proposed model can assist the consumer to optimise energy use by optimising air conditioning to avoid price spike occurrences related to the probability of an electricity price spike.

This model indicates that the outside temperature, temperature at the start of a spike and the probability of a price spike have a significant impact on the total expected market cost for operating the air conditioning. This result indicates that the consumer should apply the pre-cooling method to minimise energy costs by anticipating the electricity price spike. This is useful when a price spike occurs and when there is a substantial risk of a price spike.

Based on the result of analysis with considering to the parameters of the room and the air conditioning, and electricity market price data from the AEMO during hot days from 2011 to 2012, this model is only appropriate to define the total expected if spike may only occur exactly on the hour. This is model is no proper to estimate total expected cost for every time. However, it is recommended to the consumer to approach this model to solve the similar problem as we discussed above.

Chapter 7: Case of Optimise Energy Cost for the Air Conditioning if a Price Spike May Occur Every Five Minutes a Day

7.1 INTRODUCTION

This chapter describes the optimal solution achieved by applying the DSR model to minimise the energy cost of air-conditioning if a spike may occur any five minutes during any day. Section 7.2 describes the methodology of the case study. Section 7.3 describes the cost of spike as a function of time under DSR program. Section 7.4 describes the cost of spike as a function of time under DSR program considering to the probability spike. Section 7.5 describes result of optimisation and analysis. Finally, Section 7.6 concludes this chapter.

7.2 DESCRIPTION OF METHODOLOGY CASE STUDY 3--VARIABLE SPIKE TIME MARKET ONLY CASE

As reported in this chapter, we developed a DSR model to anticipate the scenario in which a price spike may occur at any five minutes. In this simulation, the maximum permitted temperature was chosen to be 25^{o}C and the minimum temperature was chosen as 21^{o}C. In this optimisation, there are 40 switched edges characterising switching decision. From this we can to compute the energy cost for the air conditioning. The numerical minimization was applied to find to set of edges which satisfy the constraints and provide minimum cost. In this case a prise spike may occur any five minutes during a day considering to the probability spike. The process is required to optimise the energy cost. Similar to the cases reported in the previous chapter, we only considered a spike in three categories (i.e., half hour, one hour, and one and a half hour spike) for analysis. Table 7-1 summarises the parameters of a typical room and the air conditioning as used in this optimisation.

Table 7-1: Parameters of the example room used in this analysis

No.	Parameter	Value	Unit
1	Heat transfer coefficient from floor wall and ceiling (Q)	1	W/m^2 ^{o}C
2	Total area (A)	54	m^2
3	Heat capacity of the room (H)	48	J/ ^{o}C
4	Heat transfer from the air conditioning (B)	900	W
5	Maximum temperature	25	^{o}C
6	Minimum temperature	21	^{o}C
7	Rating power of air conditioning (P)	2.6	kW
8	Number of switch change events	40	

Similar to the optimisation previously described, numerical modelling was a feasible solution to optimise the total market cost considering variations in the outside temperature and the spike probability. In this simulation, the air-conditioning controlled the temperature between the maximum and minimum permitted temperatures to keep it within the comfortable limit. As discussed in Chapter 4 (Section 4.2), the air conditioning was turned on once the temperature rose to the selected maximum temperature, then the air conditioning was turned off once the temperature dropped to the selected minimum. Due to the air conditioning being off, the inside room temperature increased and could rise to the selected maximum.

In addition, the calculation of the electricity cost was based on the air-conditioning status. The electricity cost increased when the temperature was being reduced by having the air conditioning on. In contrast, the electricity cost was not calculated when the air conditioning was off. The temperature room cycling between maximum and minimum permitted temperature continuing at all times.

As indicated in Equation (4.3) (Chapter 4), the time to obtain temperature (T) at any time t can be expressed in the following equation [96]:

$$\frac{dT}{dt} = k_1 * \left(T_o - T(t)\right) - k_2 * U \qquad (7.1)$$

If the air-conditioning status is off, then U=0 and the last term is zero. The value of the constant k1 is determined by the physical characteristics of the room. When the outside temperature is constant, the solution of this differential equation is:

$$\mathrm{T(t)} = \mathrm{T_o} + \alpha.\mathrm{e}^{-\mathrm{k}*(\mathrm{t1}-\mathrm{ts})} \tag{7.2}$$

where the value of the constant α is determined by the initial condition when $\mathrm{t_1} = \mathrm{t_s}$; then:

$$\mathrm{Ts(t)} = \mathrm{T_o} + \alpha.\mathrm{e}^{-\mathrm{k}.0} \tag{7.3}$$

$$\mathrm{Ts(0)} = \mathrm{T_o} + \alpha \tag{7.4}$$

7.3 THE COST OF SPIKE AS A FUNCTION OF TIME UNDER DSR PROGRAM

The following Figure 7-1 indicates the possible scenario of finite duration spike.

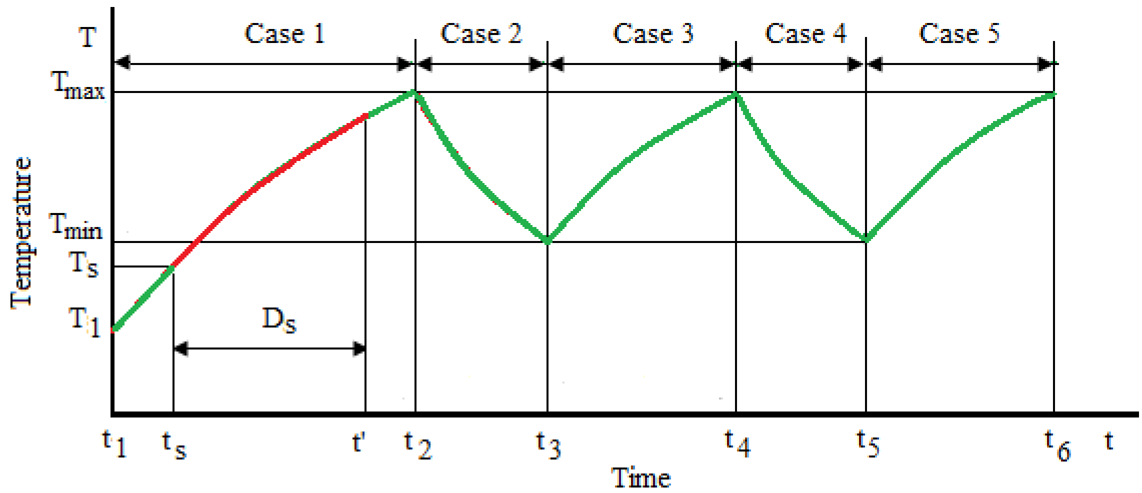

Figure 7-1: Possible scenario of finite duration spike

As described in Figure 7-1, there are several possible cases of fixed duration (D_s) spikes, such as:

$$\text{Case 1} = t_s(t) + D_s \leq t_2 \tag{7.5}$$

$$\text{Case 2} = t_2 < (t_s(t) + D_s) \leq t_3 \tag{7.6}$$

$$\text{Case 3} = t_3 < (t_s(t) + D_s) \leq t_4 \tag{7.7}$$

$$\text{Case 4} = t_4 < (t_s(t) + D_s) \leq t_5 \tag{7.8}$$

$$\text{Case 5} = t_5 < (t_s(t) + D_s) \leq t_6 \tag{7.9}$$

The market cost of the spike (MC_s), if a spike may occur at any time t, is found by multiplying the spike price (Ss) to power the air-conditioning when a spike happens (Ps) and the duration during the spike when the air-conditioning is on (D_s) at any time t, as expressed by the following equation:

$$MC_s(t) = \min \int_{t=1}^{t=n} [S_s(t) . P_s(t).\ D_s' (t). U(t)]\, dt + K \tag{7.10}$$

Subject to constraints:

$$\text{If } t_2 < (t_s(t) + D_s) \leq t_3$$

$$D_s{}' (t) = t'(t) - t_2 \tag{7.11}$$

$$\text{elseIf } t_3 < (t_s(t) + D_s) \leq t_4$$

$$D_s{}' (t) = D_s - (t'(t) - t_3) - (t_2 - t_s(t)) \tag{7.12}$$

$$\text{elseIf } t_4 < (t_s(t) + D_s) \leq t_5$$

$$D_s^{'(t)} = (t'(t) - t_4) + (t_3 - t_2) \tag{7.13}$$

$$\text{elseIf } t_5 < (t_s(t) + D_s) \leq t_6$$

$$D_s'(t) = D_s - (t'(t) - t_5) - (t_4 - t_3) - (t_2 - t_s(t)) \tag{7.14}$$

$$\text{else} \quad D_s{'}(t) = 0 \tag{7.15}$$

$$P_s(t) = \frac{P_{max} * (T_o(t) - T_l(t))}{(T_o(t) - T_{min})} \tag{7.16}$$

To determine the time of the end of the spike, at any time t, $(t'(t))$ is a function of the time of the start of the spike and the duration of the spike, as expressed in the following equation:

$$t'(t) = (t_s(t) + D_s) \tag{7.17}$$

If T_1 is the initial temperature of the room when the operation of the air-conditioning starts, and t_1 is the initial time of T_1, then the determination of the time at which the spike starts is a function of the starting temperature (Ts) as expressed in the following equation:

$$t_s(t) = \frac{t_2 - t_1}{T_{max} - T_1} * (T_s(t) - T_1) + t_1 \tag{7.18}$$

In contrast, the determination of the starting temperature (Ts) as a function of time is expressed by following equation:

$$T_s(t) = \frac{T_{max} - T_1}{t_1 - t_1} * (t_s(t) - t_1) + T_1 \tag{7.19}$$

The calculation of the time (t_2) to (t_6) to reach the maximum and minimum temperatures during the spike event is based on the differential equation as expressed in Equations (7.2) to (7.4).

7.4 COST OF SPIKE AS A FUNCTION OF TIME IN THE DSR PROGRAM CONSIDERING PROBABILITY OF SPIKE

In this simulation, the temperature room is optimised based the time of the spike. The cost is calculated based on the duration during the spike period (Ds). The cost was higher when long duration time happen in on time period. By contrast, the cost was lower when only short duration time happens in on time period. On time period mean the air conditioning status is on.

In the historical electricity market data where there are spike events (i), the probability of an event can be computed as illustrated in Equation (4.9) (Chapter 4). In this case, the probability spike may occur any five minutes any days. To consider when there is a finite probability that a price spike will occur in the system, we compute $\mathrm{MC_n}$ as the total cost without a spike occurring and $\mathrm{MC_s}$ as the total cost assuming a spike occurs. The total market cost (TMC) is thus given as the following equation:

$$\mathrm{TMC(t)} = \sum_{i=1}^{n} \mathrm{MC_{si}} * \mathrm{P_{Di}(t)} + \mathrm{MC_n(t)} * \prod_{i=1}^{n} \left(1 - \mathrm{P_{Di}(t)}\right) \qquad (7.20)$$

Subject to constraints:

$$\mathrm{MC_s(t)} = \int_{t=1}^{t=n} [\mathrm{S_s(t)} \,.\, \mathrm{P_s(t)}.\ \mathrm{D_s'}\ \mathrm{(t)}.\, \mathrm{U(t)}]\, dt + K \qquad (7.21)$$

$$\mathrm{MC_n(t)} = \int_{t=1}^{t=n} [\mathrm{S_n(t)} \,.\, \mathrm{P_n(t)}.\, \mathrm{D(t)}.\, \mathrm{U(t)}]\, \mathrm{dt} + \mathrm{K} \tag{7.22}$$

To consider if there is a probability of spike of a half hour (P_{30i}), one hour (P_{60i}) and one and a half hour (P_{60i}) duration that may occur at time t, then TMC_i is expressed by the following equation:

$$\mathrm{TMC(t)} = \sum_{i=1}^{n} (\mathrm{MC_{30i}(t)} * \mathrm{P_{30i}(t)} + \mathrm{MC_{60i}(t)} * \mathrm{P_{60i}(t)} + \mathrm{MC_{90i}(t)} * \mathrm{P_{90i}(t)}$$
$$+ \mathrm{MC_n(t)} * \prod_{i=1}^{n} (1 - \mathrm{P_{30i}(t)} - \mathrm{P_{60i}(t)} - \mathrm{P_{60i}(t)}) \tag{7.23}$$

7.5 RESULT OF OPTIMISATION AND ANALYSIS

7.5.1 Room Temperature as a Function of Time

Equation (7.1) and (7.19) were used to calculate the numerical result of room temperature as a function of time of the spike, as given in Figure 7-2.

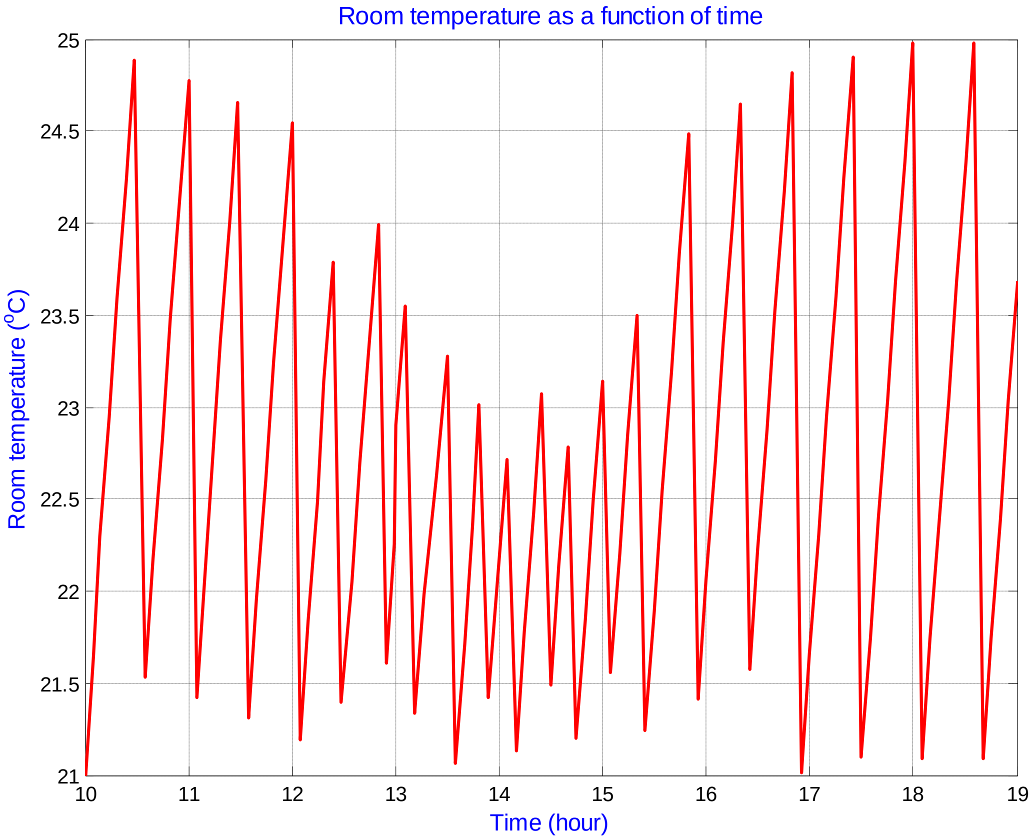

Figure 7-2: Room temperature as a function of time

Figure 7-2 presents the numerical results of the room temperature of the spike as a function of time. The results presented in the figure indicate the room temperature when a spike could happen at any 5 minutes. The initial temperature of 21°C was chosen when the spike happened at 10:00. The room temperature from 10:00 to 19:00 was cycling between 21°C and 25°C. Because the spike risk from 12:30 to 16:00 was higher, the optimal room temperature during this period was forced to be cooler than other times. The room temperature returned to the normal cycle when the outside temperature and the probability of spikes dropped to a lower level. As a result, the temperature of the room from 16:00 to 19:00 was back to the normal cycle temperature.

7.5.2 Cost of Spike as a Function Time

Equations (7.1) to (7.19) were used to compute the cost of the spike as a function of time considering the spikes of all duration (combined cases), as given in Figure 7-3.

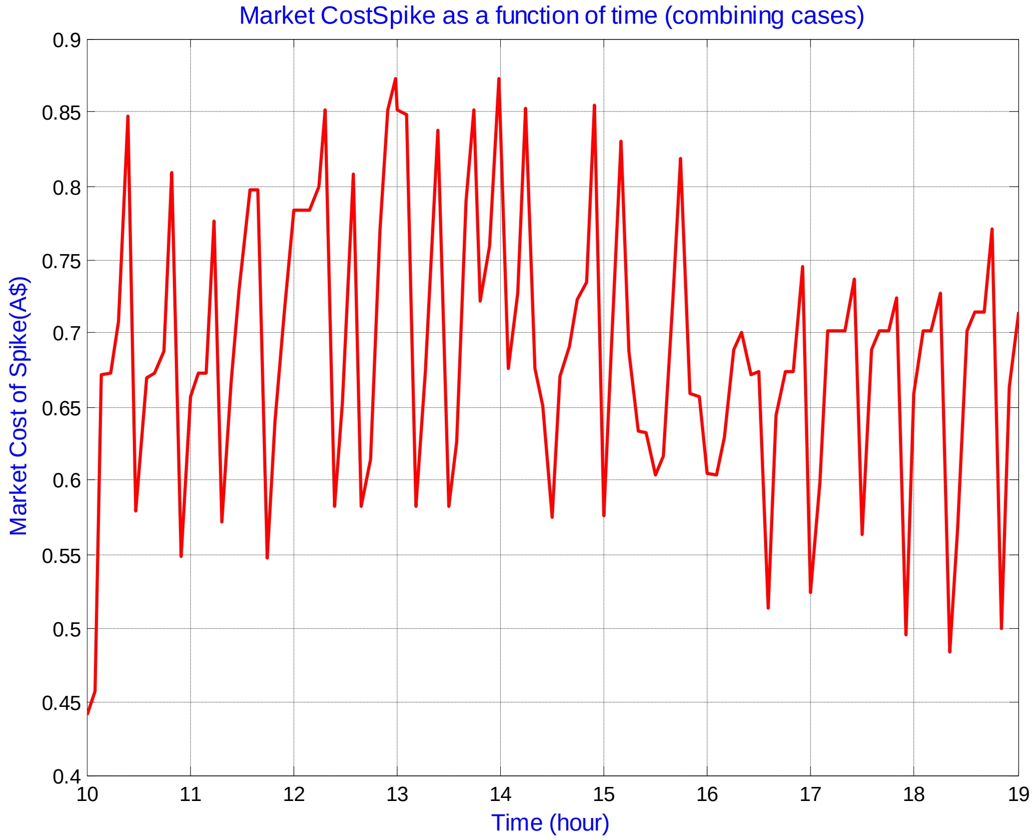

Figure 7-3: Market cost of spike as a function of time for combining cases

Figure 7-3 presents the results of optimisation for the combined cases, that is, for the half hour, one hour, and one and a half hour spikes which may occur every 5 minutes. The results presented in the figure also indicate the cost of any one and a half hour spike if it started at the given time; this cost increased when the outside temperature and starting temperature of the spike were higher. This was because the air-conditioning was optimised to operate at a low temperature level when the outside temperature was higher. In addition, the air-conditioning needed to be on for a long time when the starting temperature of the spike was higher. As a result, the cost of the spike from 13:45 to 14:15 was more expensive. The pre-cooling method was also applied to avoid a high cost when the spike happened. The high values of the spike cost justified that the pre-cooling method should be applied to minimise the energy cost.

7.5.3 Market Cost of Spike as a Function Time Considering to the Probability Spike

Equations (7.1) to (7.23) were used to compute the cost of the spike and total market cost as given in Figure 7-4 and Table 7-2.

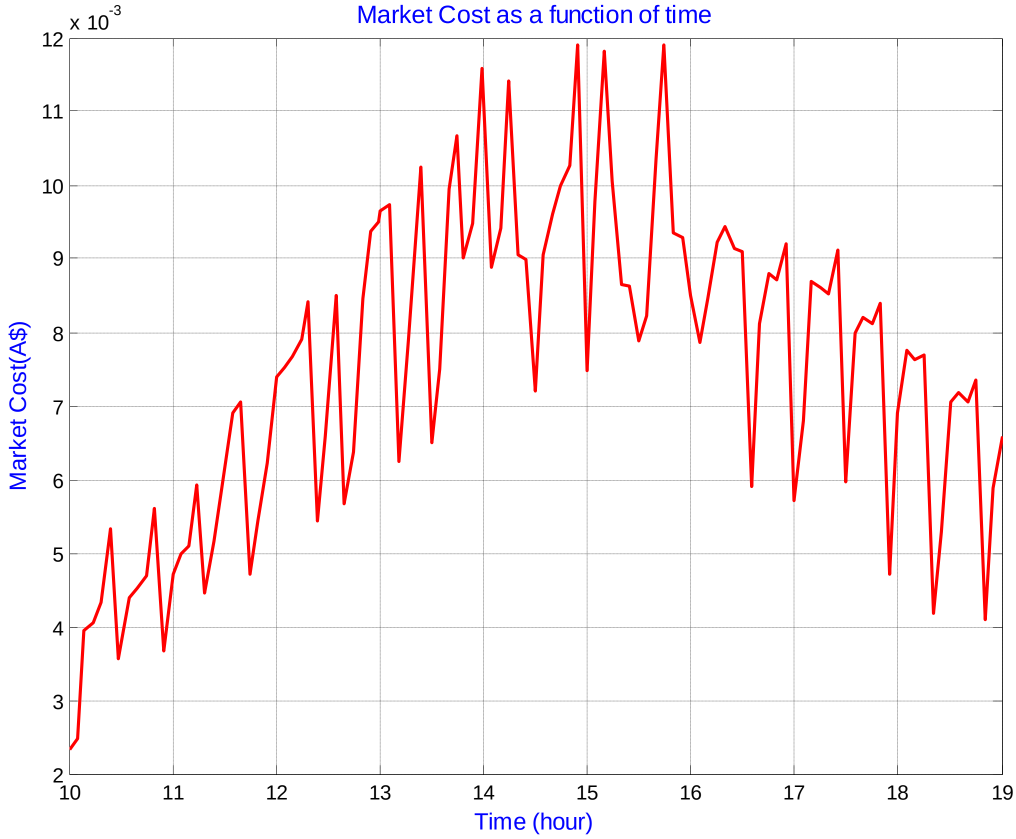

Figure 7-4: Total market cost as a function of time considering to probability

Table 7-2: Total market cost considering to the probability

TMC (A\$)	**MC_s (A\$)**	**MC_n (A\$)**
3.65	74.95	2.93

It is clear from Figure 7-4 that the cost of the spike was not just based on the outside temperature but also on the starting temperature and the probability of the spike. The cost of the spike from 13:45 to 14:15 was high because the outside temperature was higher than at any other time and the starting temperature of the spike was higher. In addition, due to the high outside temperature, starting temperature and the spike probability when the spike happened, the cost of the spike from 13:00 to 16:00 was more expensive. However, in general, the cost of the spike was similar to the pattern of the spike probability. This also indicates that the spike probability had a significant impact on defining the cost of the spike and the total cost.

7.6 CONCLUSIONS

This chapter demonstrated the proposed consumer DSR model that aims to allow consumers to independently and proactively manage air-conditioning peak electricity demand for every period based on the electricity market price. The model is applicable for both residential and commercial consumers in order to address fluctuating energy prices by optimising energy costs for air-conditioning wherein controlled tariff customers can reach a benefit-sharing arrangement with an aggregator.

This model indicates that the outside temperature, starting temperature of the spike and the probability of a price spike have a significant impact on defining the market cost of the spike and total market cost. The proposed model can assist the consumer to optimise the energy cost for air conditioning to meet a spike and spike probability cases. As a result, the energy costs are minimised. In addition, the pre-cooling method should be applied to avoid high electricity prices at critical times. However, pre-cooling is only undertaken when there is a substantial risk of a price spike.

Based on the result of analysis data indicated that this model was only appropriate if a price spike may occur any five minutes during a day considering to selected of the typical of room and the air conditioning, electricity market price data from the AEMO during weekdays on hot days from 2011 to 2012. This model is only approximate the additional cost due to a price spike during the spike time as a function of initial room temperature and outside temperature. However, this model is no calculate the exact cost if spike happen for any time during a day. While, it is recommend to the consumer to approach this model to approximation the total cost if a price spike may only occur any five minutes a day to reach collective benefit with the aggregator.

Chapter 8: Case of Optimised Energy Cost for Air-Conditioning Based on the Network Cost and Electricity Market Price

8.1 INTRODUCTION

This chapter describes the optimal solution by applying the DSR model to minimise the energy cost for air-conditioning if a spike may occur every five minutes during a day. Section 8.2 describes the methodology adopted in this case. In Section 8.3, the total cost of the peak demand based on the network cost is investigated. In Section 8.4, the total cost of the peak demand considering the probability spike is investigated. Section 8.5 presents the results of the optimisation and analysis. Section 8.6 describes the benefits of DSR for several consumers. Finally, Section 8.7 concludes this chapter.

8.2 DESCRIPTION OF METHODOLOGY CASE STUDY 4--VARIABLE SPIKE TIME NETWORK AND MARKET CASE

In this simulation, we optimised the cost of the energy used by the air conditioning considering both the network and market price. Based on the history of the peak demand, periods of peak demand because of network cost usually occurred for two hour a day during the hot days in 2011-2012. In addition, according to the duration of the electricity market price spike, there were several cases of a price spike on hot days in 2011-2012. In this research, we only considered combined cases (i.e., half hour, one hour, and one and a half hour spike cases) and the analysis considered that a spike may occur in any five minute interval. The case of a price spike of two hours or more was not considered as a significant probability based on the data analysis. The temperature data on 29 February 2012 was selected for the outside temperature (T_o).

In this optimisation process, there are 40 switch edges characterizing the switching decisions. From this we can compute the energy cost for the air conditioning. The numerical minimization was applied to find to set of edges which satisfy the constraints and provide minimum cost. This process is needed to optimise the energy cost considering to the network overload and electricity market price.

In this simulation, the starting point temperature of 21^{o}C at 10:00 was chosen. The maximum and minimum permitted room temperatures were 25^{o}C and 21^{o}C, respectively. There were 40 switch change events permitted during the 10 hours where the air conditioning operated, starting from 10:00 to 19:00, and the probability of a price spike was applied every five minutes. Table 8-1 summarises the parameters of the typical room and the air conditioning used in this optimisation.

Table 8-1: Parameters of the example room used in this analysis

No.	Parameter	Value	Unit
1	Heat transfer coefficient from floor wall and ceiling (Q)	1	W/m^{2} ^{o}C
2	Total area (A)	54	m^{2}
3	Heat capacity of the room (H)	48	J/ ^{o}C
4	Heat transfer from the air conditioning (B)	900	W
5	Maximum temperature	25	^{o}C
6	Minimum temperature	21	^{o}C
7	Rating power of air conditioning (P)	2.6	kW
8	Number of switch change events	40	

In this research, after analysis of the historical data, a threshold value of A$75 per MWh was used for analysis of the market price. This means any regional reference price of more than A$75 per MWh was called a price spike. The average electricity price under A$75 per MWh was called the no-spike price (normal price), which in this period was an average of A$30.69 per MWh. In addition, a threshold value of 5000 MW for Queensland load was used as a surrogate of a feeder network overload. This means that any demands more than 5000 MW were called an overload. In this simulation, a tariff network component of A$76.72 per MWh was used for the normal price and A$767.2 per MWh was used to indicate full price of a network overload.

8.3 PEAK DEMAND BASED ON THE NETWORK COST

Periods of peak demand are caused by many users using a lot of electricity at the same time. For example, on a hot day many households and offices will increase their air-conditioning load simultaneously, causing a sharp increase in electricity demand. Peak demand typically occurs in the afternoon when households begin using appliances such as air-conditioning, washing machines, dryers, dishwashers, televisions, ovens and computers. This is usually associated with the period from 14:00 to 16:00 on weekdays.

In the simulation in this research, peak demand penalties were justified when the demand (W) was more than the rating of the transformer (Wr). The are number of option to encourage consumer to limit the load when the feeder is overloaded. One option is to use a brick wall penalty where there is a sudden increase in the network cost as soon as the loading exceeds the transformer rating. The problem of this approach is that even if the overload is small there can be a big penalty. Alternatively, the penalty can be gradually increased as the loading exceed the transformer rating. One could apply a linear or square law when the loading exceeds transformer rating. In this research, a brick wall penalty was applied for ease of implementation. This penalty was used as the indicator for the consumer to avoid peak demand by applying the pre-cooling method.

If S_p is the network overload price when there is a substantial risk of network overload and S_o is normal price, then the network cost (NC) can be determined by the following equation:

$$\mathrm{NC(t)} = \int_{t=1}^{t=n} [(\mathrm{S(t)\,.\,P(t).\,D(t).\,U(t))}\ \ \mathrm{dt}\ + \mathrm{K}] \qquad (8.1)$$

Subject to constraint:

If W > Wr

S(t)= Sp

$$\text{Else } S(t)=So \tag{8.2}$$

The aim of the controller is to maintain the temperature of the room between the lower and upper temperatures to keep the room temperature within comfortable limits. For this purpose, the simulation starting point of 22^0C at 10:00 was chosen with the air conditioning status off. The initial value for the optimisation was for the temperature cycling between the maximum and minimum permitted temperatures.

The calculation of the electricity cost during this period was based on the air conditioning status. The electricity cost increased when the temperature was being reduced by having the air conditioning on. However, there was no electricity cost when the air conditioning was off. The electricity cost calculation included the network price.

8.4 PEAK DEMAND CONSIDERING TO NETWORK COST AND THE ELECTRICITY MARKET PRICE

The case of a finite probability that a price spike would occur on the system was considered, with S_s and S_n as the electricity market price when a spike occurs and when no spike occurs, respectively. We computed MC_n as the market cost without a spike occurring and MC_s as the market cost assuming a spike occurred; for example, a half hour duration spike (MC_{30}), one hour duration spike (MC_{60}), and one and a half hour duration spike (MC_{90}). If values are attributed to the probability of a spike of half hour (P_{30i}), one hour (P_{60i}) and one and a half hour duration (P_{60i}), and the spike may occur at time t, then the total market cost (TMC) can be expressed by the following equation:

$$\begin{aligned} TMC(t) = \sum_{i=1}^{n} (&MC_{30i}(t) * P_{30i}(t) + MC_{60i}(t) * P_{60i}(t) + MC_{90i}(t) * P_{90i}(t) \\ &+ MC_n(t) * \prod_{i=1}^{n} (1 - P_{30i}(t) - P_{60i}(t) - P_{60i}(t)) \end{aligned} \tag{8.3}$$

Subject to constraints:

$$MC_s(t) = \int_{t=1}^{t=n} [(S_s(t) \,.\, P_s(t).\, D_s^{\prime}(t).U(t))\ dt + K] \tag{8.4}$$

$$MC_n(t) = \int_{t=1}^{t=n} [(S_n(t) \,.\, P_n(t).D(t).U(t))\ dt + K] \tag{8.5}$$

$$P_s(t) = \frac{P_{max} * (T_0(t) - T_l(t))}{(T_0(t) - T_{min})} \tag{8.6}$$

$$P_n(t) = \frac{P_{max} * (T_o(t) - T_{max}(t))}{(T_o(t) - T_{min})} \tag{8.7}$$

Therefore, calculation of the total cost (TC) considering the network and market price is expressed by the following equation:

$$TC(t) = NC(t) + TMC(t) \tag{8.8}$$

When applying a DSR program, the consumers and aggregator could earn collective benefits. If the TCo is assuming the total cost without a DSR program, the TC is the total cost under a DSR program. Therefore, the collective benefit is expressed by the following equation:

$$CB = TCo - TC \tag{8.9}$$

The percentage of collective benefit is illustrated by the following equation:

$$\%\ (CB) = \frac{CB\ (A\$)}{TC_o\ (A\$)} \tag{8.10}$$

8.5 RESULT OF OPTIMISATION AND ANALYSIS

8.5.1 Cost as a Function of Peak Demand without DSR Program

Similar to the previously described method, the consumer operated the air conditioning between maximum and minimum selected temperatures. The air conditioning was turned on when the temperature rose to the selected maximum. In contrast, the air conditioning was turned off as soon as the temperature dropped to the minimum temperature. These operations were continuous without considering the network overload. Figure 8.1 shows the typical operation of the air conditioning without a DSR program and Figure 8.2 shows the total market cost and network cost without a DSR program.

Equations (7.1) to (7.19) and (8.1) to (8.7) above were used to compute the numerical results of optimisation of the air conditioning, as shown in Figure 8-1 and 8-2, Tables 8-2.

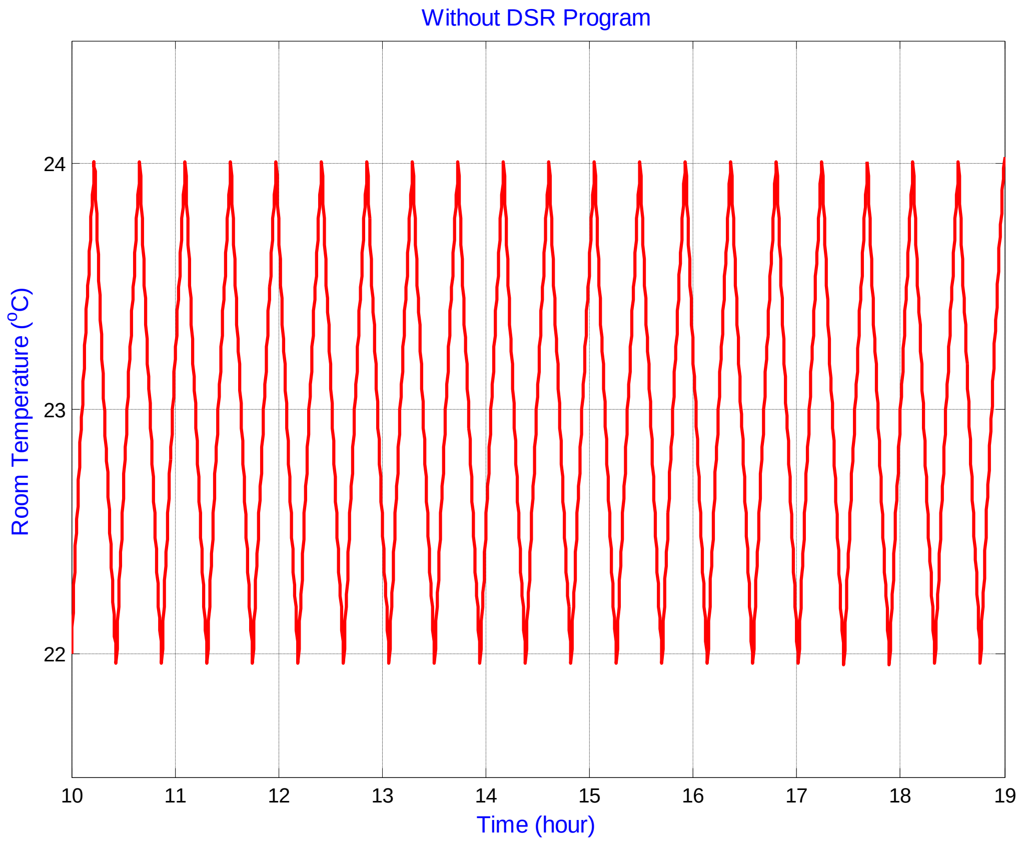

Figure 8-1: Controlling Temperature without DSR Program

Figure 8-1 indicates how the temperature was controlled without a DSR program, with the temperature being controlled between the maximum and minimum selected temperatures. The selected maximum and minimum temperatures of 24°C and 22°C were chosen. For this simulation, the starting point temperature of 22°C was chosen when the air conditioning status was off. The air conditioning was turned on when it reached the selected maximum temperature, and then was turned off when the temperature dropped to the selected minimum temperature. The cycling temperature did not consider the substantial risk of the market price and network overload. For example, a network overload occurred between 14:00 to 16:00, but the pre-cooling method was not applied in anticipation of a high price. Therefore, the consumer paid a high cost.

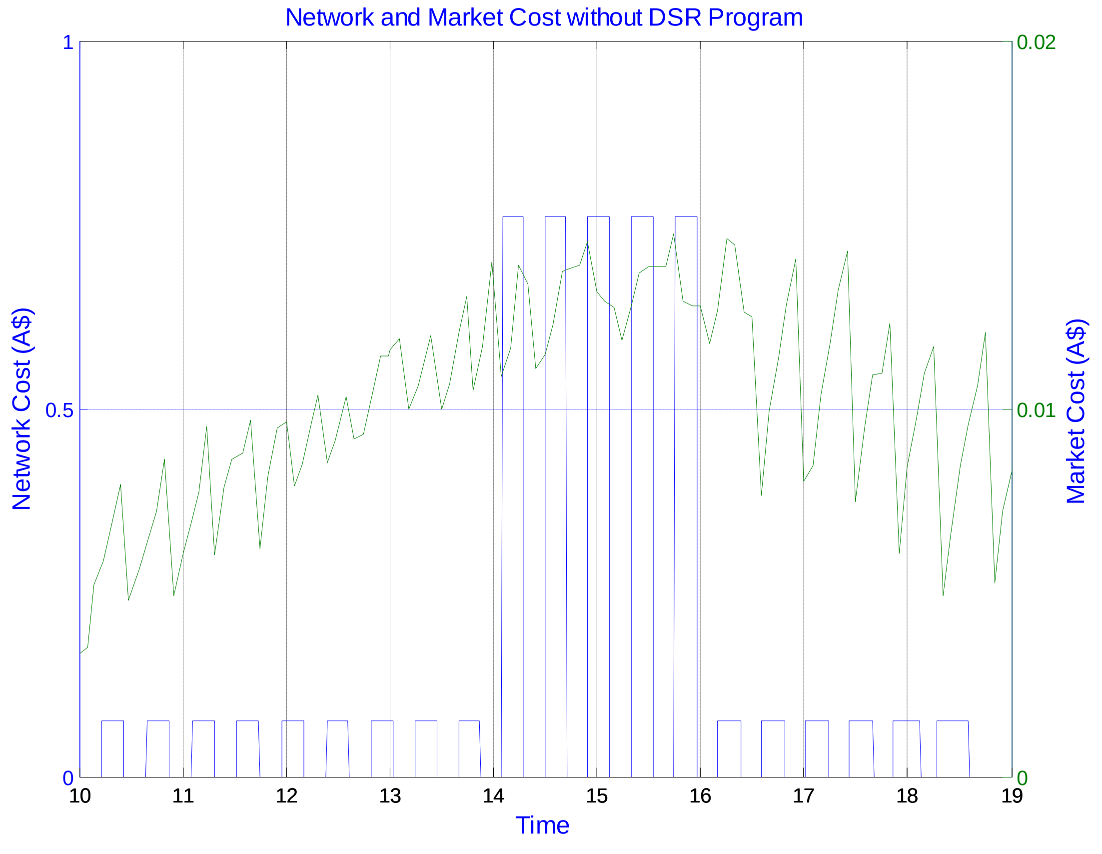

Figure 8-2: Total network and market cost without DSR Program

Figure 8-2 indicates the total cost network and market cost considering the probability that a spike would happen every five minutes during the day without a DSR program. The total market cost and network cost were expensive, as given in

Table 8.2. This was because the temperature was being controlled without a DSR program.

Table 8-2: Total cost considering both network and market cost without DSR program

TCo (A$)	NCo(A$)	TMCo(A$)
31.90	27.91	3.99

8.5.2 Cost as a Function of Peak Demand under DSR Program

The aim of the controller is to maintain the temperature of the room between the lower and upper temperatures to keep the room temperature within comfortable limits. For this purpose, the simulation starting point of 21^{o}C at 10:00 was chosen with the air conditioning status off. The initial value for the optimisation was for the temperature cycling between the maximum and minimum permitted temperatures. The maximum and minimum temperatures of 25^{o}C and 21^{o}C were chosen.

The calculation of the electricity cost during this period was based on the air conditioning status. The electricity cost increased when the temperature decreased by having the air conditioning on. However, there was no electricity cost when the air conditioning was OFF. The electricity cost calculation included the network price.

Figure 8-3 illustrates the numerical results of the air conditioning optimisation when there was a substantial risk of the peak market price due to a network overload. The cost could be minimised by maintaining the temperature of the room between the lower and upper temperatures. Equations (7.1) to (7.19) and (8.1) to (8.7) (above) were used to compute the numerical results of optimisation of the air conditioning, as shown in Figure 8-3 to 8-4 and Table 8-3.

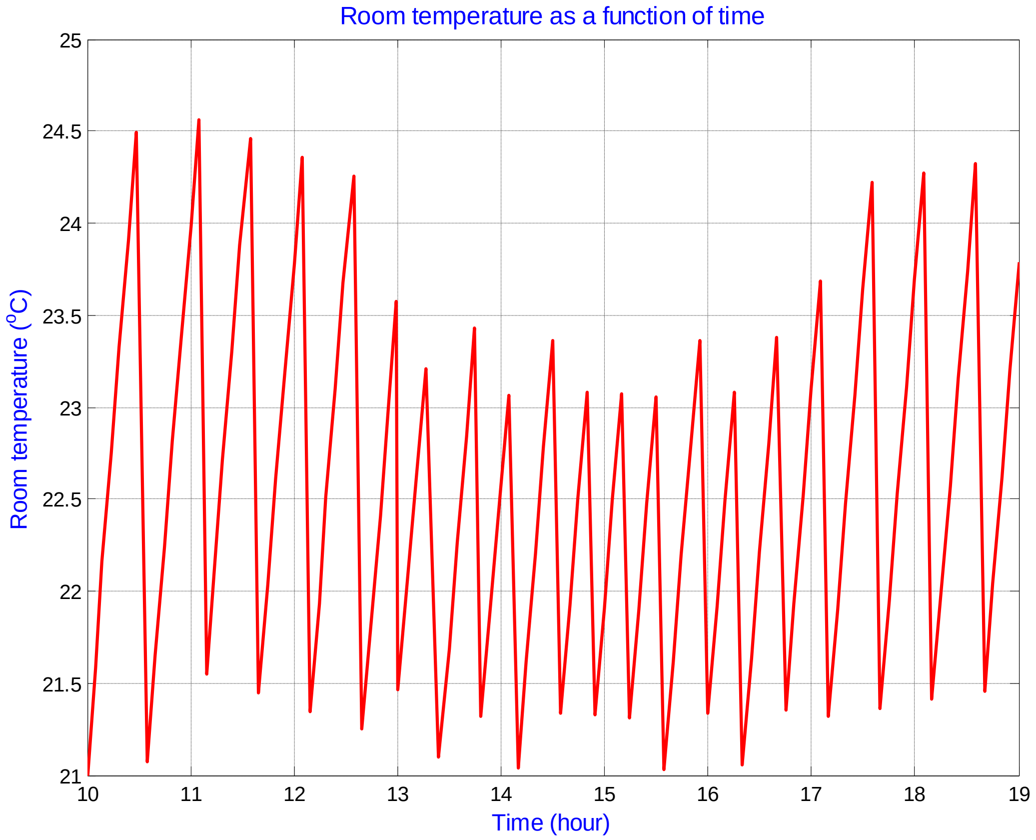

Figure 8-3: Result Optimisation of Temperature under DSR Program

Figure 8.4 indicates the network and market cost contribution from the risk of a spike as a function of time. Due to the peak demand time between 14:00 to 16:00, the network cost increased. In addition, the pattern of the market cost was similar to the pattern of the probability of the spike. Therefore, the spike probability had a significant impact on defining the cost of the spike and total cost. This cost was not just a function of the probability of a spike but also of the outside temperature. Additionally, due to the high value of the outside temperature, and the higher probability of a spike occurred from 13:45 to 14:15, the resulting cost was quite high. Equations (8.3) to (8.7) were used to compute the market cost considering the probability of a spike as given in Figure 8-4.

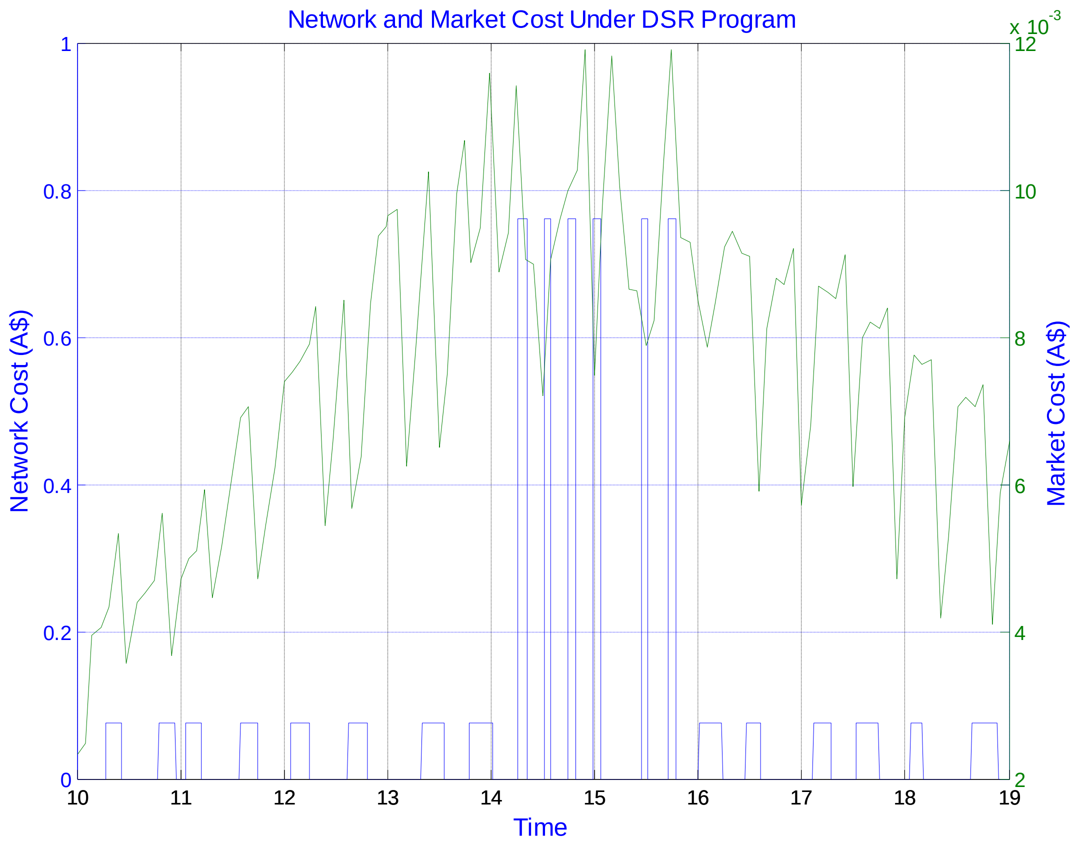

Figure 8-4: Network and market Cost of as a function of time considering to probability spike

Figure 8.4 indicates the network and market cost as a function of time considering the spike probability. The total market cost was similar to the pattern of the spike probability. However, the air conditioning was controlled with consideration of the spike probability and outside temperature. As a result, the total market cost was not similar to the total market cost without a DSR program. This was because the pre-cooling method was applied. In addition, when a network overload occurred in the system, the air conditioning was only turned on for a short time. Equation (8.8) was used to compute the total cost considering the network and market cost, as given in Table 8-3.

Table 8-3: Total cost considering both network and market cost

TC (A$)	NC(A$)	TMC(A$)
17.14	13.49	3.65

Equations (8.9) and (8.10) were used to define the collective benefit for both the consumer and aggregator. Table 8.5 presents the collective benefit for the consumer and aggregator when the consumer applied the DSR program.

Table 8-4: Collective benefit for the consumer and aggregator

Number of consumer	Total Cost			
	Without DSR TC_o (A$)	**Under DSR TC (A$)**	**Collective Benefit ($CB_{30,60,90}$)**	
			(A$)	**(%)**
Consumer-1	31.90	17.14	**14.76**	**46.26**

The analysis above indicates that the consumer could minimise the energy cost when applying the DSR program to meet peak demand considering the electricity market price or network overload. Based on the typical room and air conditioning, the collective benefit for the consumer and aggregator was A$14.76 (46.26%). This indicates the pre-cooling method was effective to minimise the energy cost.

8.6 BENEFIT OF DSR MODEL CONSIDERING THE MARKET AND NETWORK COST FOR SEVERAL CONSUMERS

In this section, we discuss the benefits of applying the DSR program for the air conditioning considering the market price and network cost for different consumers with varying room characteristics (k1). The selected k1, was based on the number of switching events by normalisation of the room temperature. The normalisation of the room temperature is the cycling temperature between the maximum and minimum room temperatures. The number of switching for every selected k1 determined the temperature cycle. The temperature was cycle between 22^{o}C to 24^{o}C for the all selected k1 without DSR program and 21^{o}C to 25^{o}C under DSR program. Table 8-5 summarises the selected k1 based on the number of switching events.

Table 8-5: Selected k1 based on the number of switching events

Number of Consumer	Number of switching	k1
Consumer-1	40	1.12
Consumer-2	44	1.26
Consumer-3	48	1.38
Consumer-4	52	1.52
Consumer-5	56	1.63

The value of the **k1** is determined by the physical characteristics of the room. If the room is large and well-insulated then it loses or gains heat slowly and the **k1** is small. If the room is small and poorly-insulated then it loses or gains heat more quickly and the **k1** is large [96].

Different k1 and numbers of switching events were selected to compare the result for every consumer. Figures 8-5 and 8-6 indicate the cycling of the temperature without the DSR program and under the DSR program based on the selected k1. Five kinds of k1 were selected, as follows: for 40 switching events the constant was 1.12, for 44 switching events the k1 was 1.26, for 48 switching events the k1 was 1.38, for 52 switching events the k1 was 1.52, and for 56 switching events the k1 was 1.63.

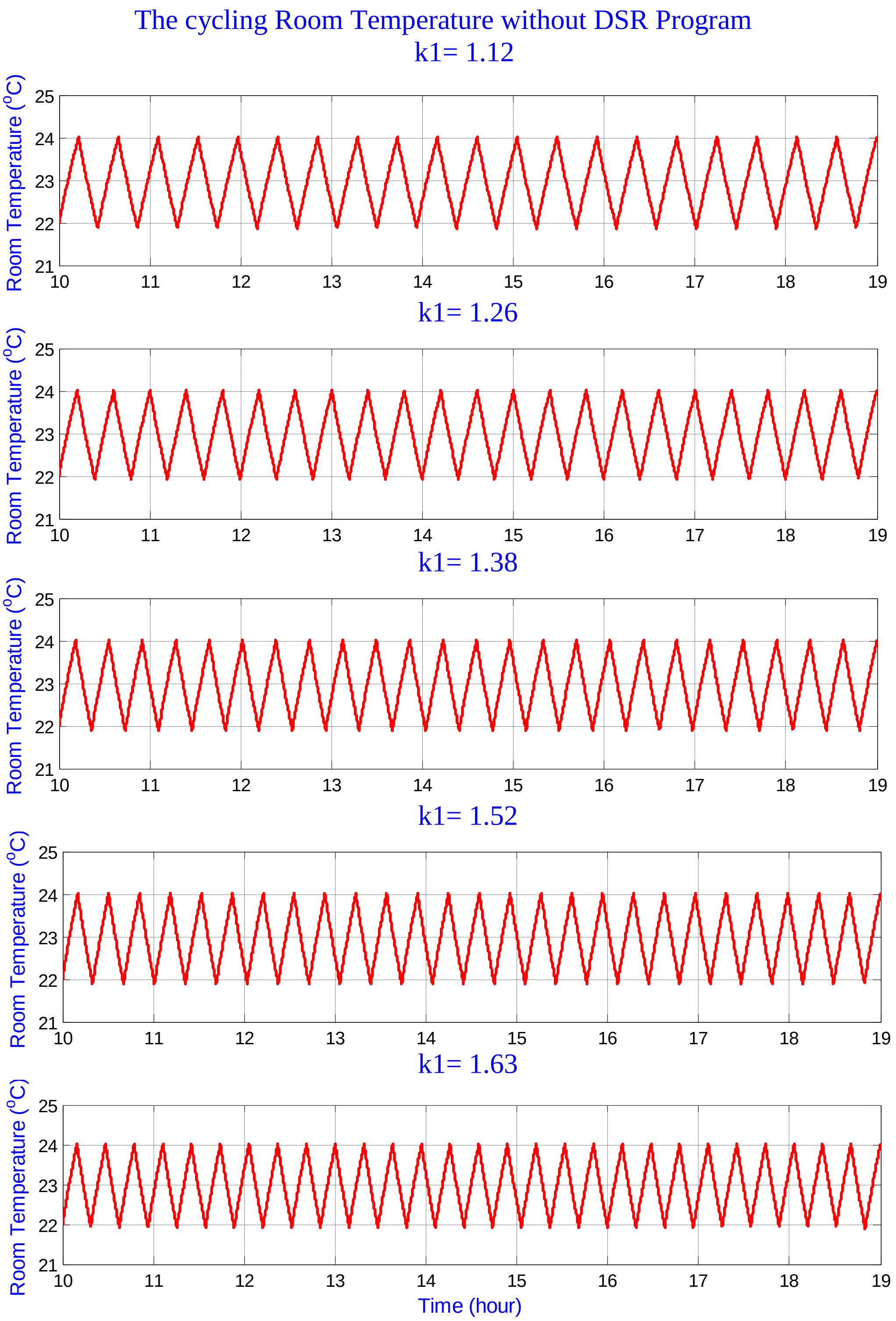

Figure 8-5: The cycling temperature for all kind of k1 without DSR program

As indicated in Figure 8-5, the normalisation of the room temperature without the DSR program was between the maximum and minimum room temperatures. The maximum room temperature was 24°C and the minimum temperature was 22°C. The temperature just cycled between the maximum and minimum without the consumer considering the substantial risk of the market price and network overload.

Based on the selected number of switching events and the k1, the cycling temperature was optimised under the DSR program. The room temperature was a function of the time of the spike considering to the substantial risk of the market price and network overload, as illustrated in Figure 8-6.

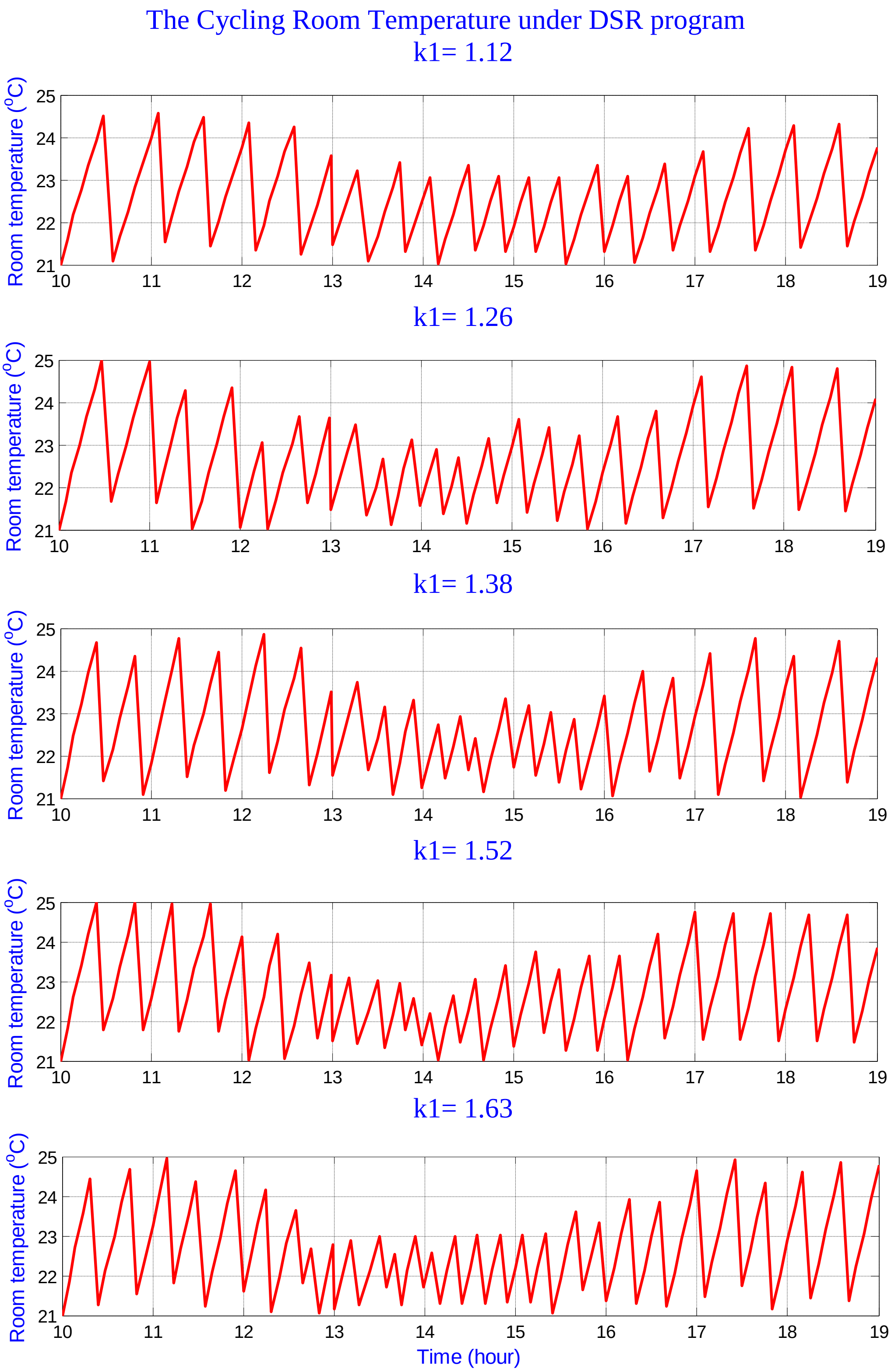

Figure 8-6: The cycling temperature for all kind of k1 under DSR program

As can be seen from Figure 8-6, the cycling temperature was kept comfortable for the consumers between the permitted maximum and minimum temperatures. Under the DSR program, the cycling temperature room become 25^{o}C and 21^{o}C. This was to give more options and flexibility in the room temperature for the optimisation. Due to substantial risk of a market price spike and the network overload considering to the probability spike, the room temperature dropped to a lower level from 12:30 to 17:00.

Equations (8.9) and (8.10) were used to define the collective benefit for both the consumer and aggregator. Table 8-6 present the collective benefit for the consumer and aggregator when the consumer applied the DSR program.

Table 8-6: The collective benefit for the consumer and aggregator

Time Constant	Total Cost			
	Without DSR TC_o (A$)	Under DSR TC (A$)	Collective Benefit (CB)	
			(A$)	(%)
Consumer-1	31.90	17.14	**14.76**	**46.27**
Consumer-2	32.31	17.35	**14.96**	**46.30**
Consumer-3	33.28	17.85	**15.43**	**46.36**
Consumer-4	34.48	18.48	**16.00**	**46.40**
Consumer-5	35.29	18.62	**16.67**	**47.24**

Table 8-6 shows the collective benefit of the consumer and aggregator based on the k1 of the room. There is a clear correlation between collective benefit for each consumer and the total cost without the DSR program and under the DSR program. The greatest collective benefit was for Consumer-5 at A$16.67 (47.24%). The second highest collective benefit was for Consumer-4 at A$16.00 (46.40%). The collective benefits for Consumer-1, Consumer-2 and Consumer-3 were A$14.76 (46.27%), A$14.96 (46.30%) and A$15.43 (46.36%), respectively.

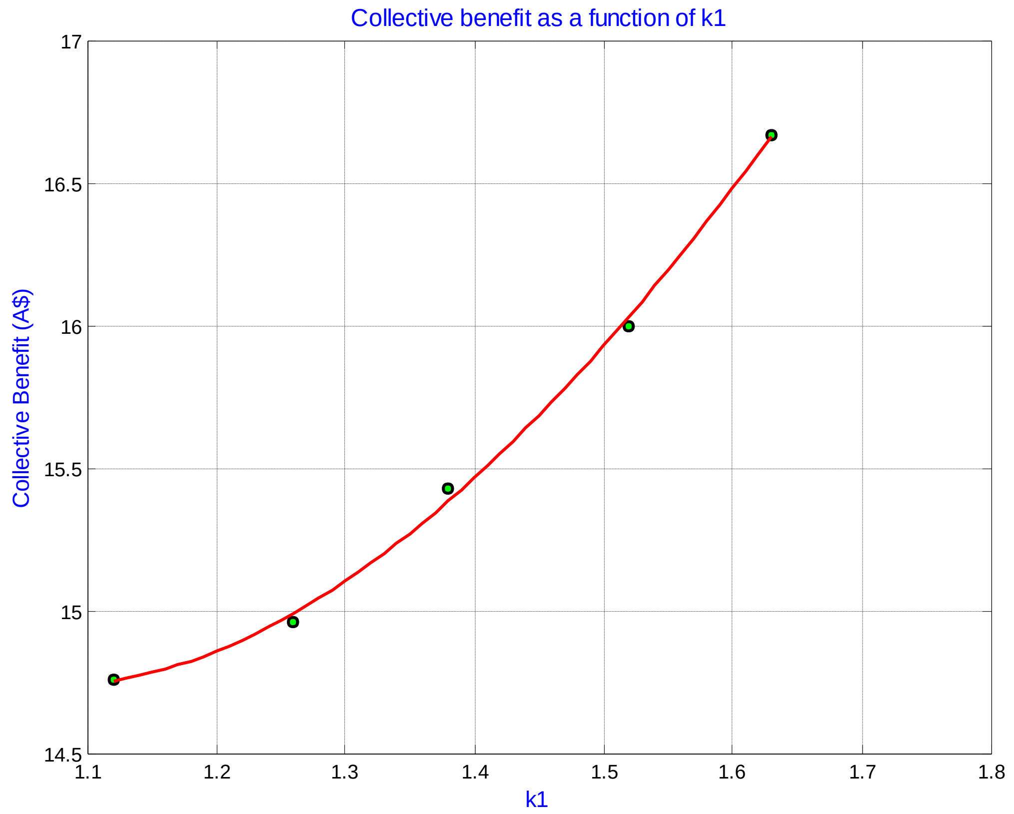

Figure 8-7: Collective benefit as a function of k1 (A$)

It can be seen from Figure 8-7 that there was a strong correlation between the number of k1 and collective benefit. The graph shows figures from the selected five k1, from 1.12 to 1.63. Due to the leaking energy factor, the highest collective benefit was reached when the k1 was higher. In contrast, a small k1 earned a lower collective benefit. Leaking energy could lead to high energy cost. As a result, the collective benefit for Consumer-5 was higher than for other consumers. In addition, the changed k1 was required to modify the number of switching events.

8.7 THE CONSEQUENCE OF CHANGING TEMPERATURE RANGE

Similar to the previously method, the numerical minimisation was applied to set up of the switching characteristic which satisfy the constraint and provide minimum cost. The following Figure 8-8 indicates the consequence of changing temperature range of permitted maximum and minimum temperature. In this optimisation, the permitted maximum and minimum temperature of 24.5^{o}C and 21.5^{o}C were chosen, with satisfy the selected of characteristic room (k1).

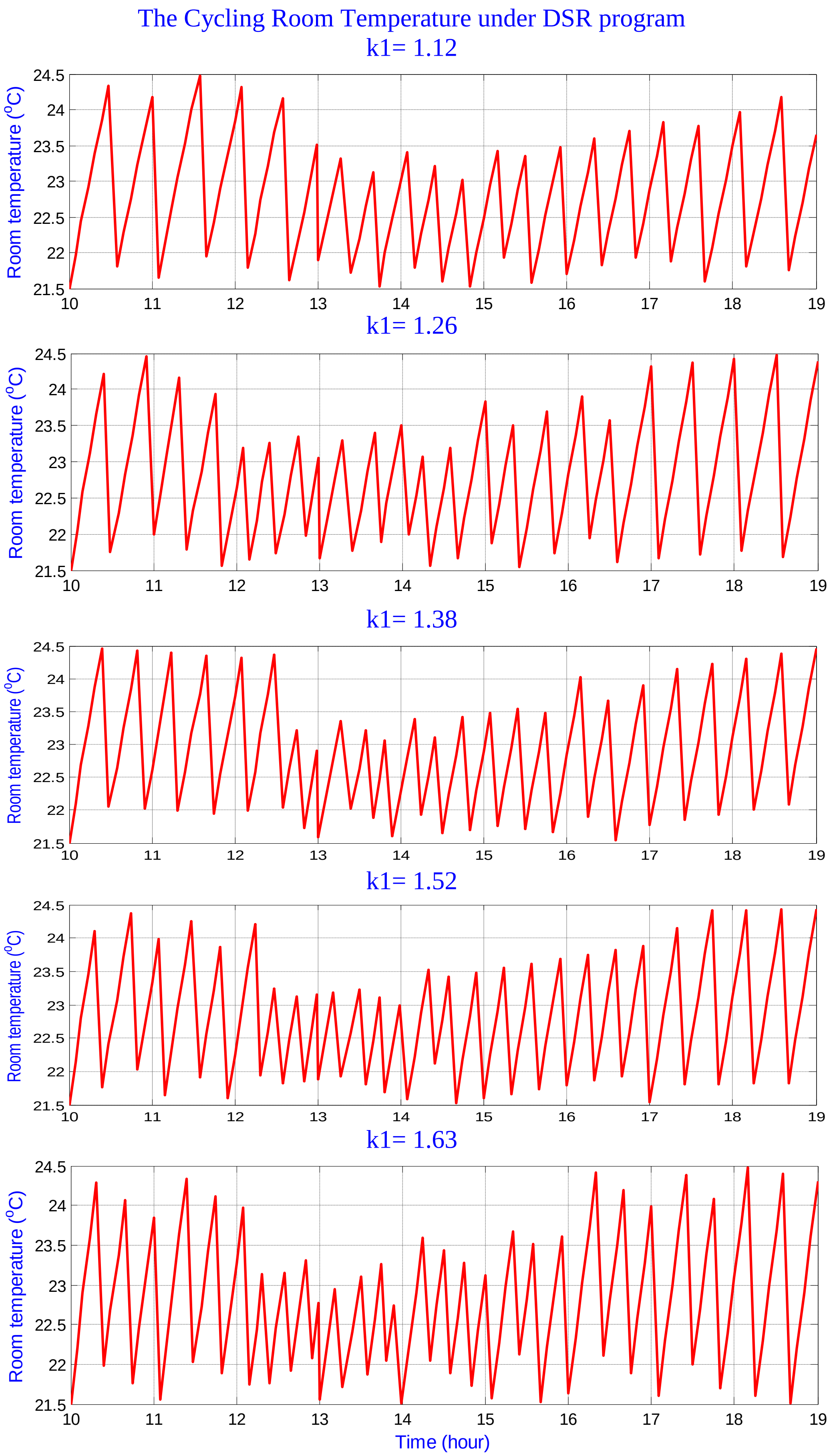

Figure 8-8: The cycling temperature for all kind of k1 under DSR program

As indicated in Figure 8-8, the control system kept the temperature between the maximum and minimum permitted temperatures. Similar to the previously described method, due to the outside temperature, the spike probability and network overload, the inside room temperature decreased to the low level between 12:30 to 17:00. In this optimisation, the temperature range was smaller than previously. Therefore, in the optimisation process the cycling temperature had limited options to find the edge of the characteristics of the switching. In addition, a different collective benefit was reached as the consequence of the variation of the temperature range.

Equations (8.9) and (8.10) were used to define the collective benefit for both the consumer and aggregator. Table 8-8 present the collective benefit for the consumer and aggregator when the consumer applied the DSR program.

Table 8-7: The collective benefit for the consumer and aggregator

Time Constant	Total Cost			
	Without DSR TC_o (A$)	Under DSR TC (A$)	Collective Benefit (CB)	
			(A$)	(%)
Consumer-1	31.90	17.37	14.53	45.55%
Consumer-2	32.31	17.58	14.73	45.59%
Consumer-3	33.28	17.99	15.29	45.94%
Consumer-4	34.48	18.63	15.85	45.97%
Consumer-5	35.29	18.94	16.35	46.33%

Table 8-7 shows the collective benefit for the consumer and aggregator based on the k1 of the room while satisfying the different ranges of the maximum and minimum permitted temperatures. The temperature range was smaller than in the previous optimisation. As a consequence, the collective benefit was smaller than the previous result (see Table 8-6). The greatest collective benefit was for Consumer-5 at A$16.35 (46.33%). The second highest collective benefit was for Consumer-4 at A$15.85 (45.97%). The collective benefits for Consumer-1, Consumer-2 and Consumer-3 were A$14.53 (45.55%), A$14.73 (45.59%) and A$15.29 (45.94%), respectively.

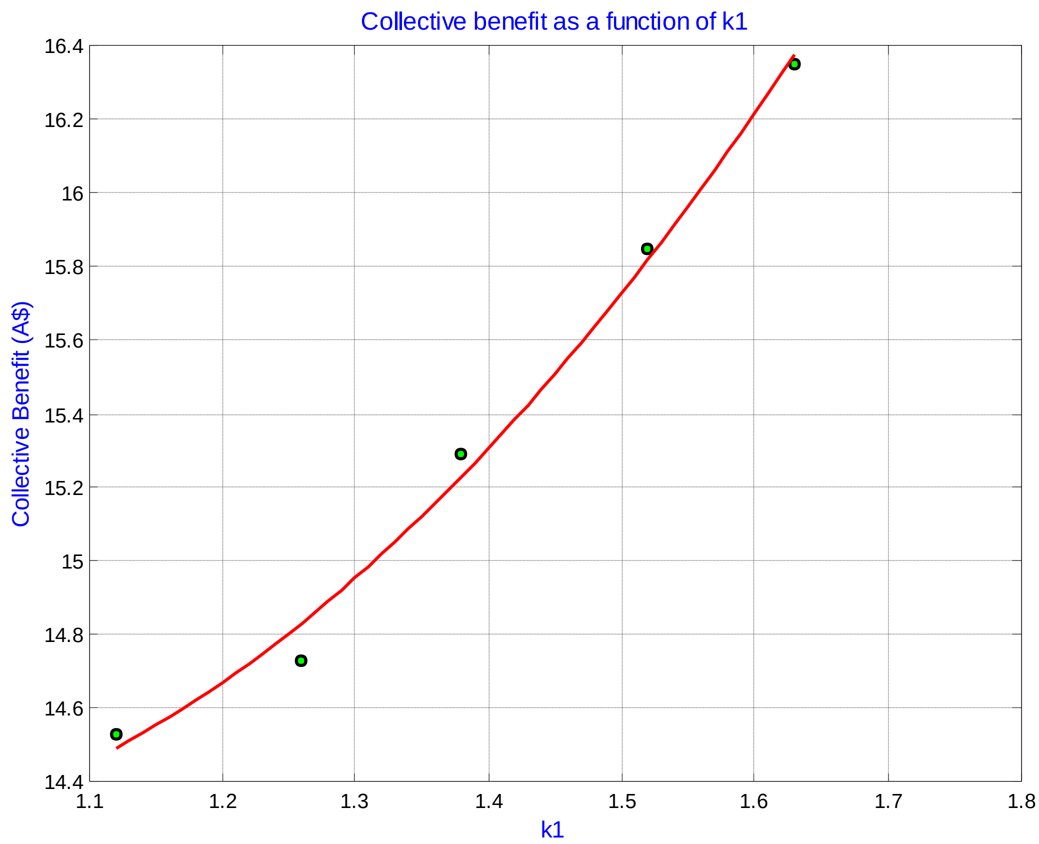

Figure 8-9: The cycling temperature for all kind of k1 under DSR program

Figure 8-9 above indicates the correlation between the number of k1 and collective benefit with different range of temperature. The smallest collective benefit was reached when the k1 was smaller. In contrast, a high k1 earned a higher collective benefit. This is because of leaking energy factor. Leaking energy could lead to high energy cost. As a consequence, the collective benefit for Consumer-1 was lower than for other consumers.

8.8 CONCLUSIONS

The discussion in this chapter has demonstrated that the proposed DSR model can be used to minimise energy cost. The proposed model can assist the consumer to optimise the energy cost for air conditioning if there is a substantial risk of the network overload or market price spike. This result indicates that, the consumer should apply the pre-cooling method to minimise energy costs by anticipating the high cost due to the network overload. This model is applicable for residential and commercial consumers to gain collective benefits for both the consumer and aggregator.

The discussion in this chapter also demonstrated the pattern of the air conditioning controlled under a DSR program when there was a substantial risk of the price spike because of the network overload. This result indicates that the outside temperature had a significant impact on defining the pattern of the temperature monitored by the control system. The control system applied the pre-cooling method before the time range of risk. This indicates that the pre-cooling method was effective. As a result, the market cost could be minimised.

This model is applicable to minimise energy costs when the spike may occur at any five minutes during the day. The results of the optimisation indicated that the spike probability had a significant impact on defining the market cost. The pattern of the market cost was similar to the characteristics of the spike probability. The market cost increased when the spike probability was higher. In contrast, the market cost decreased when the spike probability was lower. In addition, under the DSR program, the total cost was based on the k1 of the room. The total cost increased when the k1 rose.

Under the DSR program, the consumer and aggregator could earn collective benefit. The amount of collective benefit had a strong correlation with the number of k1. The typical room with low k1 had a lower collective benefit. By contrast, the typical room with high k1 could earn higher collective benefit.

Based on the result of optimisation indicated that this model is only appropriate to minimise energy cost if a price spike of electricity market cost may only occur at any five minutes during a day and network overload only occur during 2 hours from 14:00 to 16:00. This model is considering to the parameters of the room and the air-conditioning and based on electricity market price data from the AEMO on weekdays during hot days from 2011 to 2012. This model would need to change parameters to consider price spikes or network overloads at other times or weekends.

This model is only approximate the cost increases due to a price spike during the spike time and network overload as a function of initial room temperature and outside temperature. This model is no applicable to define exact total cost if a price spike may occur at any time during a day and due to network overload.

Chapter 9: Conclusions and Recommendations

9.1 SUMMARY

This thesis described a DSR model to mitigate peak demand in the electrical system. This model suggested a method of operating air conditioning in order to minimise the energy cost. The consumer should be exposed to the electricity market price data from the AEMO during the day based on information from the aggregator. The consumer may use this model to anticipate a price spike in the electricity market and a network overload. This model is applicable based on the selected typical room and air conditioning, electricity market price data from the AEMO on hot days during weekdays from 2011 to 2012. The simulations showed that the consumer could earn collective benefit along with the aggregator. As a result, potential benefits for small consumer and aggregators exist.

In this thesis, the pre-cooling method was applied to anticipate a price spike in the electricity market. The method can be recommended for small consumers to minimise the energy cost. The pre-cooling method was also used to minimise the energy cost if a price spike may occur in the middle of the day, as discussed in Chapter 5. It is important to note that the pre-cooling method was just applied when there was a substantial risk of the price spike. Based on the typical room and air conditioning, electricity market price data from the AEMO on hot days during weekdays from 2011 to 2012, the consumers and aggregator earned collective benefit if the spike may happen in the middle of the day and considering the probability spike. As a result, the cost can be minimised. However, this model is only appropriate if we know a price spike may only occur in the middle the day. Due to the unpredictable a price spike of electricity market that this model is inappropriate to solve for all problems. While, it is recommended for the consumer to apply this model to solve the problem similar with the all characteristics, as discussed in chapter 5.

The DSR model was also used to determine the total expected market price for operating the air conditioning, as discussed in Chapter 6. The pre-cooling method was required to define the minimum expected cost when an hourly spike may happen. The pre-cooling method was only justified when the total minimum expected cost reached under the expected temperature. Based on the typical room and air conditioning, and electricity market price data from the AEMO on hot days during weekdays from 2011 to 2012, the consumer should apply this model to define the expected cost to avoid a price spike in electricity market. This model indicated that the outside temperature, temperature at the start of a spike and the probability of a price spike had a significant impact on the total expected market cost for operating the air conditioning. However, this model is only appropriate to define the expected cost when hourly spike time may occur. By contrast, this model is not suitable to define the total expected cost when a price spike may occur at any time during a day. Although, it is recommended to approach this model to define the expected cost if hourly spike may occur considering to the similar characteristic of the room, the air conditioning and electricity market and temperature data, as described in chapter 6.

The DSR model was also used to minimise energy costs for the air-conditioning if a spike may occur at any five minutes during any days, as discussed in Chapter 7. It is recommended that the consumer applies the pre-cooling method to anticipate that a price spike may occur any five minutes during any days. As a result, the cost can be minimised. In addition, based on the typical room and air conditioning, electricity market price data from the AEMO on hot days during weekdays from 2011 to 2012, the consumer could earn a collective benefit by applying this DSR model. However, this model is only proper to the similar problem as discussed in chapter 7. A price spike may only occur at any five minutes during a day. This model is only approximate the additional cost due to a price spike during the spike time as a function of initial room temperature and outside temperature. However, this model is no calculate the exact cost if spike happen for any time during a day.

Finally, the DSR model was applied to minimise the energy cost for the air conditioning if there was a substantial risk of the network overload and market price spike, as discussed in Chapter 8. The DSR model was able to formulate the significant impact of the spike probability and outside temperature to define the total cost. The pre-cooling method was required to anticipate high costs due to the substantial risk of the market price and network overload. As a result, collective benefits could be earned by the consumer and aggregator by applying this model. In addition, it was found that the collective benefit had a strong correlation with the number of constant k1. This model was appropriate based on the typical room, air conditioning and on electricity market price data from the AEMO for hot days during weekdays from 2011 to 2012. This model is appropriate to apply if a price spike may occur any five minutes during a day and network overload just conducted within 2 hours between 14:00 to 16:00. This model is no applicable to apply if a price spike may occur any time during a day and network overload happen any time during a day. This model is only approximate the cost increases due to a price spike during the spike time and network overload as a function of initial room temperature and outside temperature. This model is no applicable to define exact total cost if a price spike may occur at any time during a day and due to network overload.

9.2 RECOMENDATION FOR FUTURE WORK

Possible paths for future work include:

- Using the DSR model to investigate the potential collective benefit if there is substantial risk of the price spike or network overload on hot days during weekends to find the total benefit through the year
- Using the DSR model to investigate the potential collective benefit if there is a substantial risk of the price spike or network overload during all days to find the total benefit through the year.
- Using the DSR model to investigate the potential collective benefit if there is a substantial risk of the price spike or network overload during all months of the year to find the total benefit through the year.
- Integrating the DSR model and renewable energy sources to anticipate the spike probability during the whole day.

- Using the DSR model to anticipate the spike in the electricity market price and network overload due to the use of other appliances (e.g., heater, washing machine and refrigerator).

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